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# Kernel selection in statistical femur modeling

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**W**e aim to contribute to the development, analysis, and assessment of the statistical femur model when combined with a set of different analytical kernel functions. Reported results demonstrate the superior performance of data-driven femur model (computed from a few femur examples) when combined with an anisotropic kernel. These femur models have great potential for surgery applications.

## 1 Introduction

The topic of this paper is the construction of the femoral Statistical Shape Model (SSM) from a limited number of data for surgical applications to build a patient-specific femur model and to plan implant placement. Most of the current models are based on deep learning and trained on big data. However, in medical image analysis despite the large anatomical variations in size and shape, sometimes only a few medical data are available. In this context, statistical models have demonstrated to be promising [1, 2]. The main goal of SSMs is to build a flexible shape model using the statistics computed from a set of shape instances. Many variants of SSMs exist in the literature [3]. Among them, the Point Distribution Model (PDM) [4] is the most known. Considering a set of aligned and in correspondence shapes, PDMs model the shapes as a normal distribution of point variations. Gaussian Process Morphable Models (GPMMs) [5] are the generalization of PDMs which model shapes by deformations from a reference shape. GPMMs offer more flexibility in defining covariance (also known as ‘kernel’) function than in PDMs. This paper describes the impact of using different kernel functions in GPM-based modeling of the morphological variation of femurs. Performances on a femur dataset are presented.

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## 2 Materials and methods

### 2.1 The Femur Dataset

Our dataset was generated using cadaveric femurs which were scanned at the University Hospital of Brest (CHRU Brest). It consists of a set of 13 femur meshes (about 116k points per mesh) and their corresponding landmarks (6 anatomical landmarks per femur, similar to Albrecht et al. [6]). The dataset was shuffled and partitioned into two groups: 9 meshes as training and 4 as the test set. To perform this study Scalismo framework [7] was used.

### 2.2 Shape Modeling Pipeline

Figure 1 shows the global femur modeling pipeline. The first step consists in preprocessing to make the meshes in our training dataset rigidly aligned using landmarks and scaled using bounding box information of femurs. Next step is establishing the dense correspondences among the meshes. This step is crucial and involves: Firstly, the rigid registration to build the unbiased reference mesh using IMCP algorithm [8] followed by the screened poisson surface reconstruction algorithm [9]. The reference mesh was decimated to about 5k points. Secondly, the non-rigid registration which involves the construction of the ‘deformable femur model’ using the unbiased reference mesh with smooth Gaussian deformation assumption. The Gaussian deformation kernel parameters were considered as  $s:100$  and  $\ell:100$ . The ‘deformable femur model’ was fitted to each of the aligned and scaled meshes using non-rigid ICP algorithm based on Gaussian Process (GP) regression. The fitting Root Mean Square Error (RMSE) in this step was computed as  $1.22 \pm 0.09$  mm. The fits (i.e., the set of fitted ‘deformable femur model’ to the meshes in the training set) were considered as the ‘in correspondence mesh set’. It consists of the aligned, scaled and in correspondence mesh data. It was used to

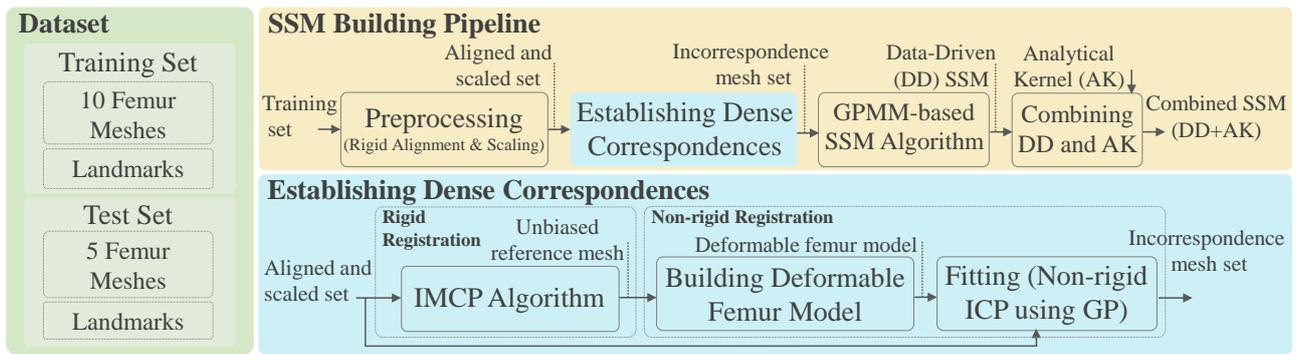


Figure 1: The shape modeling pipeline.

Table 1: Comparison of employed kernel functions.

Kernel func.	Parameters
Data-driven	Computed from 9 samples
Gaussian	$s:50 \ell:50$
Multiscale	$s_1:50 \ell_1:200, s_2:200 \ell_2:50$
Anisotropic	$s_x:50 \ell_x:50, s_y:50 \ell_y:50, s_z:200 \ell_z:200$

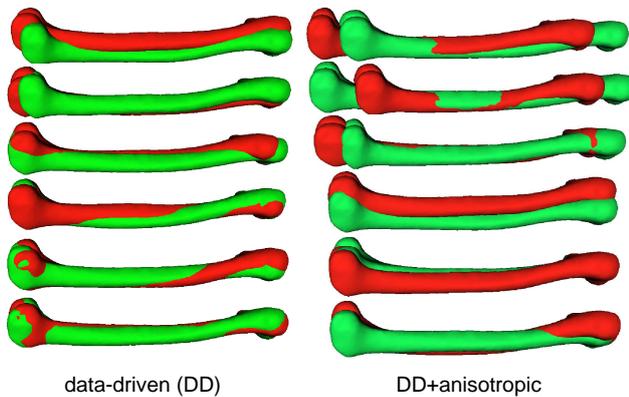


Figure 2: Six dominant modes of variation of the data-driven model and its combination with the anisotropic kernel. Represented in red and green are the variation of the mean femur by three times standard deviations along eigenmodes.

build the ‘data-driven model’ using GPM-based SSM algorithm [5]. The next step was the combination of ‘data-driven model’ with the defined analytical kernel functions (see Table 1). The Gaussian kernel was defined by  $k(x, x') = s e^{-(x-x')^2/\ell^2}$ , where  $s$  is the scale and  $\ell$  indicates the length-scale (the influence radius of the kernel). The multiscale kernel was constructed by the summation of 2 Gaussians. The anisotropic kernel was defined as having more variation in the length direction of the femur. The kernels were low-ranked using the 10 prominent basis functions.

### 3 Experiments and results

Experiments were carried out for a comparative study to evaluate the model performance when combined with the specified kernels. The evaluation is performed by

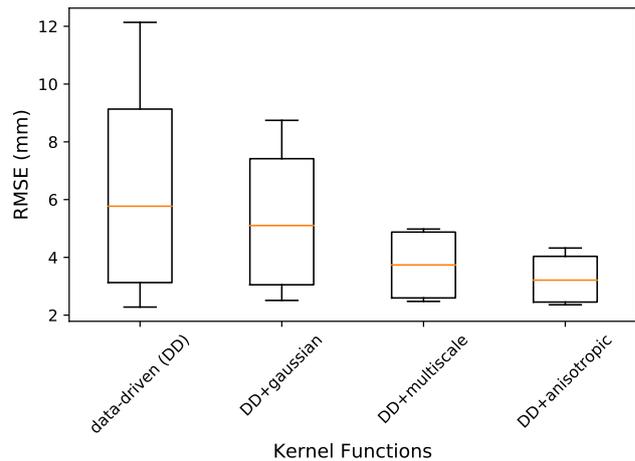


Figure 3: Evaluation of different kernel functions.

fitting the SSMs to mesh data in the test set and then computing RMSE of the fitted femur models to the test set. Figure 2 shows some modes of the data-driven SSM and its combination with the anisotropic kernel. Results for comparing the SSMs can be seen in Fig. 3. The RMSE for the data-driven SSM and its combination with the Gaussian, multiscale and anisotropic kernels were computed as  $6.48 \pm 4.53$ ,  $5.36 \pm 2.98$ ,  $3.73 \pm 1.36$  and  $3.27 \pm 1.00$  mm, respectively.

### 4 Discussion and conclusion

The current study developed SSMs for femur bone modeling based on GPMs. Out of different analytical kernels (Gaussian, multiscale and anisotropic kernels) and keeping the 10 most prominent basis functions, it has been found that the combination of our data-driven model with the anisotropic kernel more accurately encodes the patterns of variability of femurs in our dataset. Specifically, we observed that the modes of data-driven SSM when combined with the anisotropic kernel corresponds well with the actual deformation of the femur bone (this can be confirmed by seeing how the dominant modes vary in Figure 2). Exploration of other customized kernels or transferring the knowledge of femur variations from a larger dataset can be considered for future works.

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