43075 Probabilistic Shape Modelling

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Exercise 2 — Normal distributions, Gaussian processes and rigid Alignment

Introduction	19. March 2019
Deadline	**2. April 2019** (Discussion / presentation during exercise session)

1. Femur project: second step

The goal of this exercise is to perform the second step of the femur project, which you started in the last exercise. This time, you will build a femur shape model based on smooth deformations defined by a Gaussian Process. This model will later be useful in the final step. Start by reading the instructions in Step 4.11: "Femur Project: First Steps", in week 4 on FutureLearn.

Evaluation: Before designing your Gaussian process, think about properties of the model, which allow you to decide whether your model is a good model of the femur shape or not.

Experiment: Once you know what you are looking for, build different Gaussian process models and visualize them. Explore the shape variability by drawing random samples and visualizing shape variability (using ScalismoUI).

Make at least the following experiments:

1. Explore different parameters of the Gaussian kernel (scale s and smoothness σ). How do they affect the shape variability?
2. Try varying the number of basis functions used in your low-rank approximation of the Gaussian Process (e.g. 1, 10, 100, 200). See how this affects the flexibility of the model. Can you explain what is happening?
3. Design a kernel, which ensures that the deformations are more pronounced along the longitudinal axis of the femur.
4. Combine kernels with different scale and smoothness. Should the scale be large for the smooth kernels and small for the less smooth ones, or is it vice versa? What happens to the shape variability if you add up these kernels?

2. Theory questions

Think about the following questions:

Learned vs. Designed Kernels

We can build a Gaussian process by specifying a Gaussian kernel as a covariance function. Why would we still use example data to build our shape models?

Smoothness of the Gaussian process

How does the smoothness of a kernel (i.e. the parameter σ of the Gaussian kernel) influence the number of basis functions, which are needed to approximate a given Gaussian process? Can you explain this?

Representations of Gaussian processes

What are the advantages and disadvantages of the parametric (low-rank) representations of a Gaussian process.

Shape models from limited data

What problems can occur when a Statistical Shape Model is built from a dataset with a small number of example data? Give three differnet possibilities how this problem can be alleviated.