EPiC Series in Health Sciences
Volume 5, 2022, Pages 69–72
Proceedings of The 20th Annual Meeting of the International Society for Computer Assisted Orthopaedic Surgery

3D reconstruction of joints from partial data using multi-object-based model: Towards a patient-specific knee implant design

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Abstract

In clinical routine, the capture of three-dimensional (3D) bone geometry is crucial for surgical planning, implant placement and postoperative evaluation. Nevertheless, accurate 3D reconstruction of the knee joint for the estimation of patient-specific features remains a challenge, although it has been widely studied. In this context, statistical shape models (SSM) have been used to reconstruct a global shape from partial observations, based on their ability to capture the anatomical variation from different patients. However, these studies incorporate single object SSMs which limit their application for analyzing local bone morphology and thus they lack the capacity to analyze the human anatomy at the joint level. In this paper, we present a multi-object based framework for the 3D reconstruction of the knee joint using a dynamic multi-object Gaussian process model (DMO-GPM) and an adapted Markov Chain Monte Carlo (MCMC) based model fitting algorithm.

The knees were reconstructed with an average mean square error of 1.81 ± 0.37 mm and maximum error of 3.31 mm corresponding to the surface-to-surface distance between the predicted and original knees. The results show that the knee is accurately reconstructed, especially around the joint contact surfaces. This is crucial because most of the patient-specific features required for the implant design, use landmarks in this area. The results suggest that the approach is robust and accurate to design personalized knee implants.

1 Introduction

Three-dimensional (3D) reconstructions of knee bones can be used for surgical planning, premorbid shape estimation, and personalised implant design [1]. However, reconstruction of partial bone structures resulting from fractures, image acquisition protocols, or disease remains challenging. In this context, statistical shape models (SSM) have been used to reconstruct a global shape from partial observations [4], [5] based on their ability to capture the anatomical variation from different patients. However, these studies incorporate single object SSMs which limit their application for analyzing local bone morphology and thus they lack the capacity to analyze the human anatomy at the joint level.

In this paper, we present a multi-object based framework for the 3D reconstruction of the knee joint using a dynamic multi-object Gaussian process model (DMO-GPM) [3] and an adapted Markov Chain Monte Carlo (MCMC) based model fitting algorithm. This reconstruction takes into account the shape correlation between the femur and tibia and requires the pose initialisation of only one of them.

2 Method

2.1 Dataset and Knee model training

The data consisted of 3D mesh surfaces of femur and tibia manually segmented from computed tomography (CT) angiography images of the bilateral knees of individuals acquired at the University Hospital Center of Brest, France. Institutional ethics approval was granted for this study (Approval No: 2018CE.49/1). A total of 48 non-pathological knee joints were used from 24 patients presenting variation in knee morphology and flexion.

In order to build the knee model, correspondence was established across the training data. To establish such a correspondence across mesh surfaces, template meshes were used to register all the samples across the datasets while preserving the pose of tibia relative to the femur using a parametric registration algorithm [2, 4]. Once correspondence was established, the knee DMO-GPM [3] was built using femur as a fixed object.

2.2 Fitting knee model onto partial data

Let us consider a target partial knee with arbitrary position of the tibia relative to the femur. The goal of the MCMC fitting process is to find the best knee DMO-GPM parameter θ that optimally represents the target example.

Let $T_o = (T_o^{femur}, T_o^{tibia})$ be the partial knee with T_o^{femur} and T_o^{tibia} representing the partial femur and tibia, respectively. The 3D reconstruction of knee joint is defined as the posterior model estimated using the Bayes rule:

$$p(\theta \mid T_o) = \frac{p(T_o \mid \theta)p(\theta)}{p(T_o)} \tag{1}$$

where $p(T_o)$ is intractable, $p(\theta)$ is the model and $p(T_o \mid \theta)$ the likelihood.

The normal distribution is used as a proposal in the Metropolis-Hastings algorithm. This proposes new samples (parameters) of the model which are accepted or rejected according to their associated probability. The accepted samples are used to build the chain and the sample with highest probability is selected as the best reconstruction of the knee joint.

3 Results

First, we evaluated the model performance in providing a statistical analysis space for knee shapes and their spatial orientations through generation of samples. Figure 1 shows variations

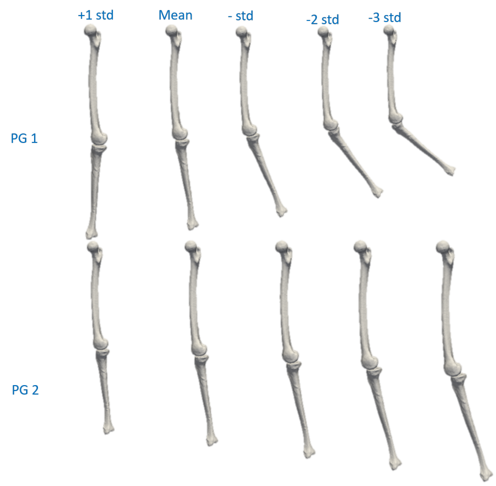

Figure 1: Knee DMO-GPM sampling. The variation (+1 to −3 standard deviation from the mean) along the first (left) and second PG (right) of the DMO-GPM of the knee joint.

(+1 to −3 standard deviation from the mean) along the first and second principal geodesics (PG) of the DMO-GPM of the knee joint. The first PG mainly explains the flexion motion of the knee and the second PG, the change in length for femur and tibia. Flexion and length changes account for the greatest variability captured by the model.

Second, we evaluate the full knee reconstruction from 7 unseen patients. The experiment was designed to reflect what clinicians face when planning prosthetic implant surgery. For patient-specific implant design, accurate measurements are required, for which preoperative partial CT images are used to extract them. Finally, the full 7 knee joints were cut and only distal and proximal femurs and tibias used (Fig. 2 on the left).

The reconstruction was done using the DMO-GPM knee and the MCMC fitting process (Fig. 2 in the middle). The knees were reconstructed with an average mean square error of 1.81 ± 0.37 mm and maximum error of 3.31 mm corresponding to the surface-to-surface distance between the predicted and original knees represented by a colormap (Fig. 2 on the right).

4 Discussion

Three-dimensional reconstruction is a key step in patient-specific implant design and clinical follow-up. While the interactions between bones and joints contribute to our daily physical activities, combining them into a single representative and robust model has not been encountered in the literature [1]. Single object models are ubiquitous in the literature and have proven successful in reconstruction tasks. However, reconstructing a 3D bone using multiple single bone models can lead to significant errors. Figure 2 shows that the knee is adequately reconstructed, especially around the joint contact surfaces. An accurate reconstruction around this area is crucial because most of the patient-specific features required for the implant design use landmarks in this area. This suggests indeed that a unified modelling approach is suitable for such reconstruction scenarios. An advantage of the reconstruction using the DMO-GPM of the knee is that the approach maintains the statistics of the variation of a single bone, so the reconstruction of the model based on a single object [6, 5] can still be done using our framework.

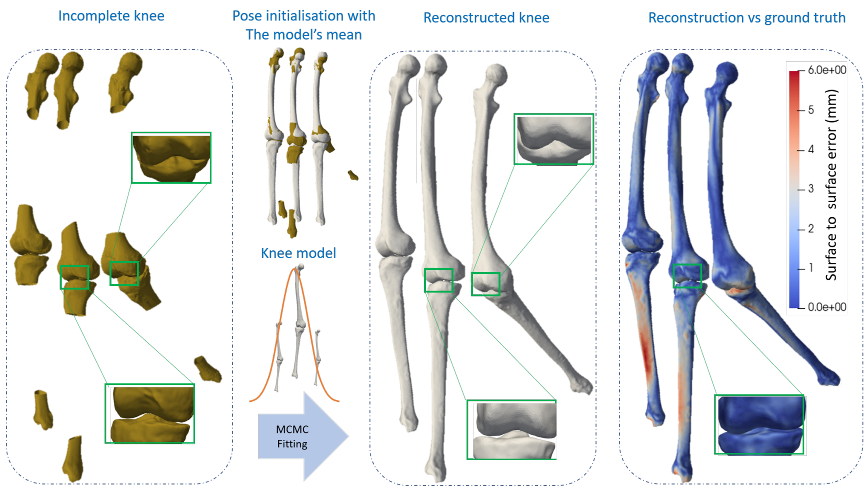

Figure 2: Reconstructed knee. From left to right: Partial knee joints, Incomplete knee joints aligned with the model mean for the initialization of the pose and knee DMO-GPM used in fitting process, reconstructed knees with associated errors. Maximum errors (red) are located on the missing diaphyses.

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