A System for Unsupervised Extraction of Orthopedic Parameters from CT Data

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Abstract: The request for software assistance is increasingly gaining importance in the field of orthopedic surgery. In the near future more people will need implants, which have to last longer. New developments in computer assisted therapy planning promise to significantly reduce the number of revisions and increase the longevity of an implant. For example the computation of the functional outcome of a total knee replacement by prediction of kinematics may provide important guidance during surgery. Speed, accuracy and as little manual interaction as possible are the key factors to make those new developments available to the clinical routine. To reach this goal we present a software assistant for the reconstruction of individual anatomical models (e.g. geometry and landmarks) from medical image data, which is an essential step in this effort. We will present and discuss present and future application scenarios.

1 Introduction

An important part of orthopedic surgery is the correct interpretation of the patient-specific anatomy. Joint replacement surgery, for instance, requires detailed knowledge and understanding of the morphology of the bone and anatomical and mechanical axes to restore the correct alignment of the joint. In today's clinical routine the choice of the appropriate endoprosthesis (size and design) and the implantation parameters (position and orientation) is largely based on the experience and training of the surgeon [MBR$^+$06]. In recent years image guided surgery (IGS) has shown to provide an improvement to conventional surgery by generating a surgical plan based on patient-specific anatomical features [BPT$^+$04] (e.g. landmarks). However, future applications in computer assisted surgery will provide more sophisticated methods to plan and predict the surgical outcome [BAGD07]. Biomechanical simulations [STM$^+$07] or virtual planning of operations [STM$^+$07], for example, require individual anatomical models, which have to be extracted from medical image data. The extraction process is often performed in a time-consuming manual or semi-automatic manner, making an application in clinical routine impracticable [PMK04].

We present a system to make those individual anatomical features readily available for therapy planning in orthopedics. This includes automatic segmentation and reconstruction of patient-specific geometrical models, especially the bony anatomy of the lower limb, as well as anatomical landmarks of the respective anatomical region. Our software assistant for decision support in orthopedic surgery is based on ZIB-AMIRA [SWHC05], a software for scientific visualization and data analysis (see http://amira.zib.de/).

This work is structured as follows: First we will discuss related work with similar methodology or application scenarios in Section 2. Then we will explain the composition of our system and recapture the previously published methods, which form an integral part of the system. In Section 4 achieved results and applications are presented after which we conclude our work with a discussion on the clinical relevance.

2 Related Work

Automatic segmentation Methods for segmentation of musculoskeletal structures of the human anatomy received much attention during the last decades. Especially the delineation of bone in CT data is a well studied topic. An overview of knee segmentation methods is given in [STZ06]. Fripp et al. [FCWO06] apply statistical shape models for the reconstruction of the knee bones. Haas et al. [HCS$^+$08] developed a coarse to fine approach for automatic segmentation of the pelvic region, i.e. parts of the pelvic bones, the proximal femur and surrounding soft tissue). A non-rigid registration of a reference dataset for the segmentation of pelvis and femur was proposed by Pekar et al. [PMK04]. The semi-automatic segmentation of the pelvis was described in [LSHD04], where a statistical shape model of the pelvic bones is adapted to the image data to perform a segmentation. In a similar approach Chintalapani et al. [CES$^+$07] describe a method for the generation and validation of a statistical shape model of the pelvis, which is also used for segmentation.

Landmark extraction In recent years the extraction of anatomical point landmarks was addressed by a number of works. An image-based method was introduced by Betke et al. [BHT$^+$03]. A template matching scheme is applied to detect point correspondences in lung CT images. Izard et al. [IJS06] compute landmarks based on a tissue-probability map learned from manually defined landmarks, which is later aligned to image data. A more complex method was proposed by Dikmen et al. [DZZ08]. Spatial relations and image features of training landmarks are learned and extracted from image data using methods from machine learning. By fitting 3-dimensional (3D) parametric deformable models to medical image data, Wörz and Rohr [WR06] extract anatomical point landmarks. In the context of an orthopedic planning scenario, Ehrhardt et al. [EHPP04] introduced a voxel-atlas based on a non-rigid registration approach for the detection of pelvic landmarks and image segmentation in CT data.

In this work we introduce a fully automatic expendable framework to extract different types of anatomical models, e.g. anatomical surface models and anatomical point landmarks, from medical image data. The approaches have previously been published and in their combination proven to offer a general framework for the extraction of relevant anatomical features [SKH$^+$08, SKH$^+$09].

3 Materials and Methods

The structure of our system for segmentation and landmark extraction is as follows (cp. Figure 1): Statistical shape models (SSMs) of the structures of interest are used throughout the whole pipeline starting with a global detection in the image data. This spatial initialization is followed by an adaptation of the SSM to the image data. The resulting output surface can be applied to anatomical landmark extraction.

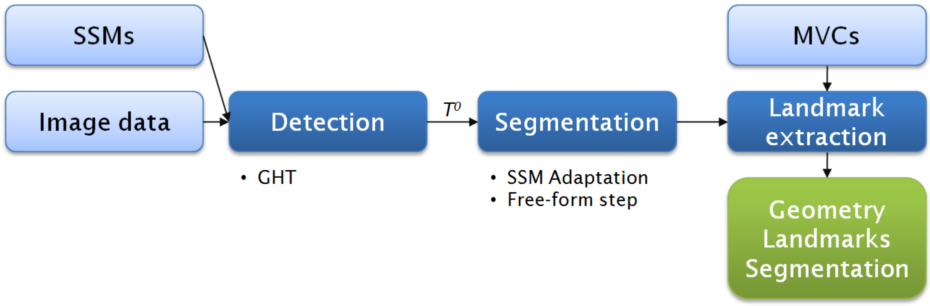

Figure 1: Principle work flow of our framework: In a first step the input SSM is spatially initialized within the patient's image data using the Generalized Hough Transform (GHT). The resulting transformation T^0 is used as initialization for $S(b, T^0)$. After alignment and optional free-form deformation of the SSM to the image data, the result surface can be used to extract anatomical landmarks previously defined by means of Mean Value Coordinates.

Our software assistant is completely embedded into the software ZIB-AMIRA integrating single steps of our framework, like initialization or SSM-based segmentation, on a modular basis. Since ZIB-AMIRA is highly scriptable, all available modules can be combined to reproduce the workflow presented in Figure 1. Another advantage of this concept is the exchangeability of single modules within the pipeline, e.g. replacement of SSMs or adaptation strategies, which allows for a fast adaptation to new application scenarios. So called sub-applications or scripting within ZIB-AMIRA can be used to integrate a network of modules into an easy to handle user interface.

3.1 Statistical Shape Models

Besides the medical image data, our system takes statistical shape models of the structures of interest as input. Those models are generated semi-automatically following the approach by [LLS02]. Such a model can be generated from a set of training surface meshes with corresponding surface points and has the form

$$S(\mathrm{b}, T) = T(\overline{v} + \sum_k b_k \mathrm{p}_k) \tag{1}$$

where $\overline{v} \in \mathbb{R}^{3m}$ represents the mean shape, $p_k \in \mathbb{R}^{3m}$ the modes of shape variation, m being the number of sample points used to discretize the shapes, $b_k \in \mathbb{R}$ are the shape weights and T is an affine transformation.

For recent applications in the field of orthopedic planning we generated a set of SSMs of relevant anatomical structures of the lower limb, e.g. pelvic bones, femur, tibia or fibula (see Figure 2 for examples). Once created, those models may be extended by additional training shapes or directly be applied to different application scenarios.

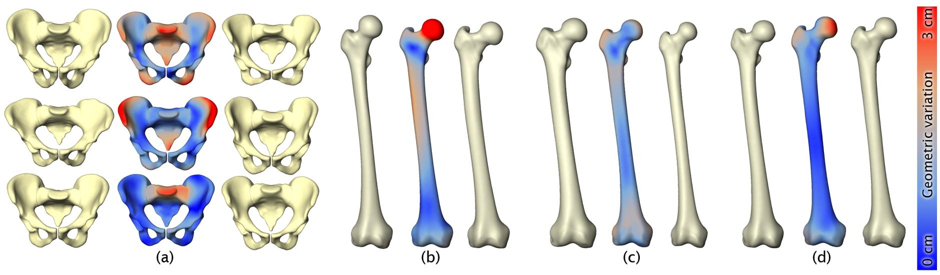

Figure 2: Statistical shape models of the pelvic bones (a) and the right femur (b-d). For both structures the first three modes of shape variation are displayed with the geometric variation color encoded on the mean surface. First to third shape mode: pelvis(top-bottom), femur (b-d).

3.2 Automatic Segmentation System

For a single structure of interest our segmentation approach can be divided into three steps, namely (1) finding the correct position and orientation of the anatomical structure within the image data (detection), (2) adaptation of the available SSM to the image data driven by image features (SSM adaptation) and (3) a free-form deformation to allow for segmentation of structures that cannot be described by $S(\mathrm{b}, T)$ (free form step). See [SKH$^+$08] for a detailed description of each step.

Detection To detect an object within the image data we apply an extension of the Generalized Hough Transform in 3D space [Kho07]. The best fit of a shape template in the image data is determined by comparing its surface normals with the available image gradients. For this task the average shape $\overline{v}$ can be used as shape template, since this instance of $S(\mathrm{b}, T)$ promises to capture the most shape variation occurring in the respective training dataset. The resulting position and orientation of the shape template gives us a rigid transformation T^0, which is used to spatially initialize the SSM.

SSM adaptation The second stage of the segmentation process is the iterative adaptation of the SSM parameters (b, T) to match the image data (see Figure 3). For this task at each step of the iteration a displacement vector field for all points of S is computed generating the target surface R^*. Extracting the displacement vector field is performed by evaluating image features along profiles normal to the surface. The generated surface R^* is then projected back onto the SSM by a least squares approximation between the shape model and R^*. This guarantees that the result is contained within $S(\mathrm{b}, T)$ and should be a valid representation of the anatomical structure described by the model.

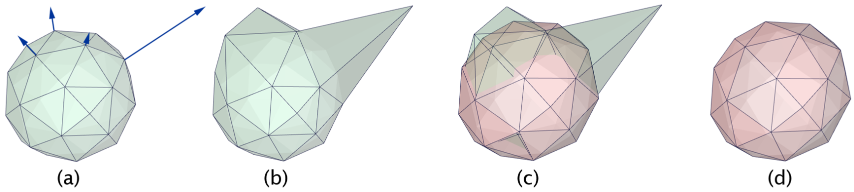

Figure 3: SSM adaptation for one time step i: Computation of the displacement vector field (a), and generation of target surface R^* by adding displacement field (b), back-projection of R^* into model space (c) and intermediate surface $S(\mathrm{b}^{i+1}, T^{i+1})$.

Free form segmentation Due to the shape variations occurring in human anatomy, an SSM is unlikely to capture those shapes exactly that are not contained in the training data. For this task we adopted two different strategies. One is based on a rather simple approach allowing for free deformation of the surface points towards image features under heuristic shape preserving and smoothing constraints [KLL07]. The second, more robust, approach exploits methods from optimal graph searching theory. At each vertex a cost profile normal to the surface is established. Then the global optimal surface (in terms of cost) is calculated by using maximum flow algorithms [KLZH08]. The graph construction also allows for the definition of smoothness and shape preserving constraints.

3.3 Landmark Extraction

As a last optional step our framework allows for an automatic extraction of anatomical landmarks. We apply Mean Value Coordinates (MVCs) in $\mathbf{R}^3$ introduced by Floater et al. [FKR05], which can be used to manually define anatomical landmarks relative to a given triangular control mesh. This control mesh can be any anatomical shape represented by a statistical shape model (see Figure 4(a and b)). By adapting this reference shape to patient's image data the landmarks are transferred to the patient-specific anatomy by interpolation using MVC (see Figure 4(c)). In addition, the linear character of MVCs and a consistent surface mesh of the training surfaces allows for an easy combination of mean value weights w_j from different shape instances (see [JSW05] for details on the computation of w_j). To minimize the influence of outliers of the manually defined training landmarks it is possible to define landmarks on multiple instances of $S(\mathrm{b}, T)$ and average them.

$$v = \frac{\sum_j \bar{w}_j p_j}{\sum_j \bar{w}_j} \quad \text{with} \quad \bar{w}_j = \sum_{k \in K} w_j^k \tag{2}$$

with K being the set of training surfaces used as landmark reference, w_j^k the j-th Mean Value weight of the k-th training dataset , and p_j the vertices of the reconstructed surface mesh.

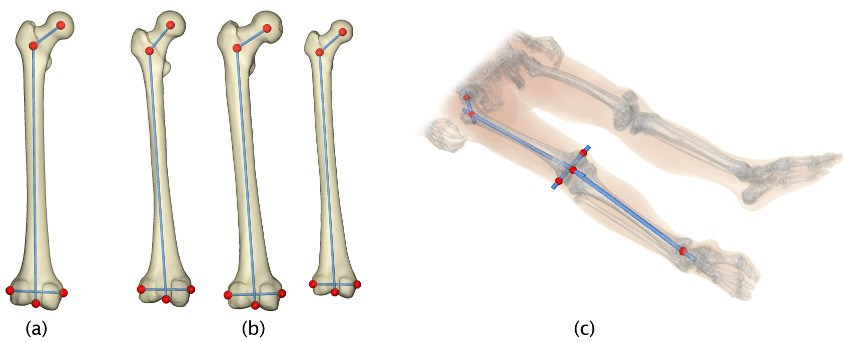

Figure 4: Average shape model of the femur with landmarks (red) relative to the surface (a). Changing the shape parameters (b, T) morphs the landmark and axes geometry by means of MVCs (b). Adaptation of the model to image data allows for direct extraction of the given landmarks (c).

4 Results and Applications

In this Section we will present some areas of application, where our fully automatic system was applied successfully.

Pelvic bones For applications in orthopedics (e.g. implant planning or osteotomies) and oncology (e.g. radio therapy planning) it is essential to know the morphology of the pelvic bones. Like presented in [HEPP01] an implant may virtually be implanted preoperatively to find the optimal implantation parameters. For the fast and accurate reconstruction of the individual pelvic anatomy in a large scale study we applied our automatic system to CT data of the pelvic region [SKH$^+$08]. An SSM of the pelvic bones, namely left and right ilium as well as the sacrum, was used to segment the input data in a fully automatic manner. The time for reconstruction was reduced from up to multiple hours to approx. 4 minutes without necessary user interaction. Our method outperformed results from similar (semi-automatic) studies in terms of accuracy.

Joint regions The anatomy of joints and their correct geometric modeling plays a major role in biomechanical simulations. The solution of contact problems using finite element methods depend on a consistent geometry, which is intersection free and an accurate representation of the patient's anatomy. Using a combined SSM of the pelvic bones and the complete femur within our framework we could present a robust and accurate method for the segmentation of the hip joint [KLZH09]. This coupled approach allows for the segmentation of image data with low slice resolution where a distinction of tissue boundaries is hardly possible.

Landmarks An area which is highly relevant in today's clinical routine is the extraction of anatomical point landmarks. This information can be used to determine anatomical and mechanical axes as well as reference systems to assess the relative positions of single anatomical structures. Such measures enable the orthopedic surgeon to detect changes in anatomy and the resulting biomechanical conditions, which might be caused by disease or as a consequence of surgery. Although the manual extraction of those landmarks can typically be achieved in a few minutes for single subjects, this procedure is prone to intra- and inter-observer variability. In addition larger studies ($n > 100$) on human morphology are only possible with automatic extraction methods generating reproducible results. We applied our system to CT data of the pelvic region to automatically extract three anatomical point landmarks defining the anterior pelvic plane, necessary for referencing the orientation of the acetabulum [SKH^{+}09]. Our automatic approach generated results comparable to that of human experts on 100 datasets with a processing time of only a few minutes.

Ligament attachment sites Besides the reconstruction of bony anatomy, soft tissue plays an import role within the musculoskeletal system. New techniques in biomechanical engineering require a representation of the complete system to validly predict the functional outcome of orthopedic surgery. For example ligaments and tendons are responsible for the transfer of forces during simulation. Without proper knowledge of the exact location and shape of the ligament or tendon attachment site, a functional prediction is unlikely to produce a valid solution. Unfortunately those structures are hardly detectable in CT data, even by expert radiologists. We adopted our framework to extract bony anatomy including the 3D shape of ligament attachment structures from CT data of the knee [SLZ08]. This was done by a modification of the SSM, where the attachment sites of interest marked on the training surfaces are part of the statistical shape analysis.

An example for the combination of bone segmentation and landmark extraction of the lower limb can be seen in Figure 5. Here, our system is utilized within the EU Project DeSSOS (FP6 IST Project 027252), concerned with the optimization of implantation parameters for total knee replacements.

5 Conclusion

We presented a software assistant for automatic extraction of patient specific anatomical features (i.e. geometry and landmarks) for application in orthopedics. Our system significantly reduces manual interaction times for the segmentation of anatomical structures. Regarding the fact that our system does not need human intervention, the effective manual effort reduces to nearly zero depending on the further processing of the results. Segmentation accuracy and landmark extraction quality are comparable to that of human experts. We applied our framework to different anatomical structures of the human musculoskeletal in different application scenarios to show its generality. Since the process does not require any supervision our system is a first step in making new promising technologies for computer assisted therapy planning in orthopedics available to the mass market.

In the future we are going to adapt our framework to new requirements arising from current or upcoming developments in the field of prediction of functional outcome of orthopedic intervention. This includes extension of the adaptation strategies and the SSM database to new structures like muscles or ligament and tendon geometry. This will allow for the direct export of *simulation ready* anatomical models for biomechanical simulation.

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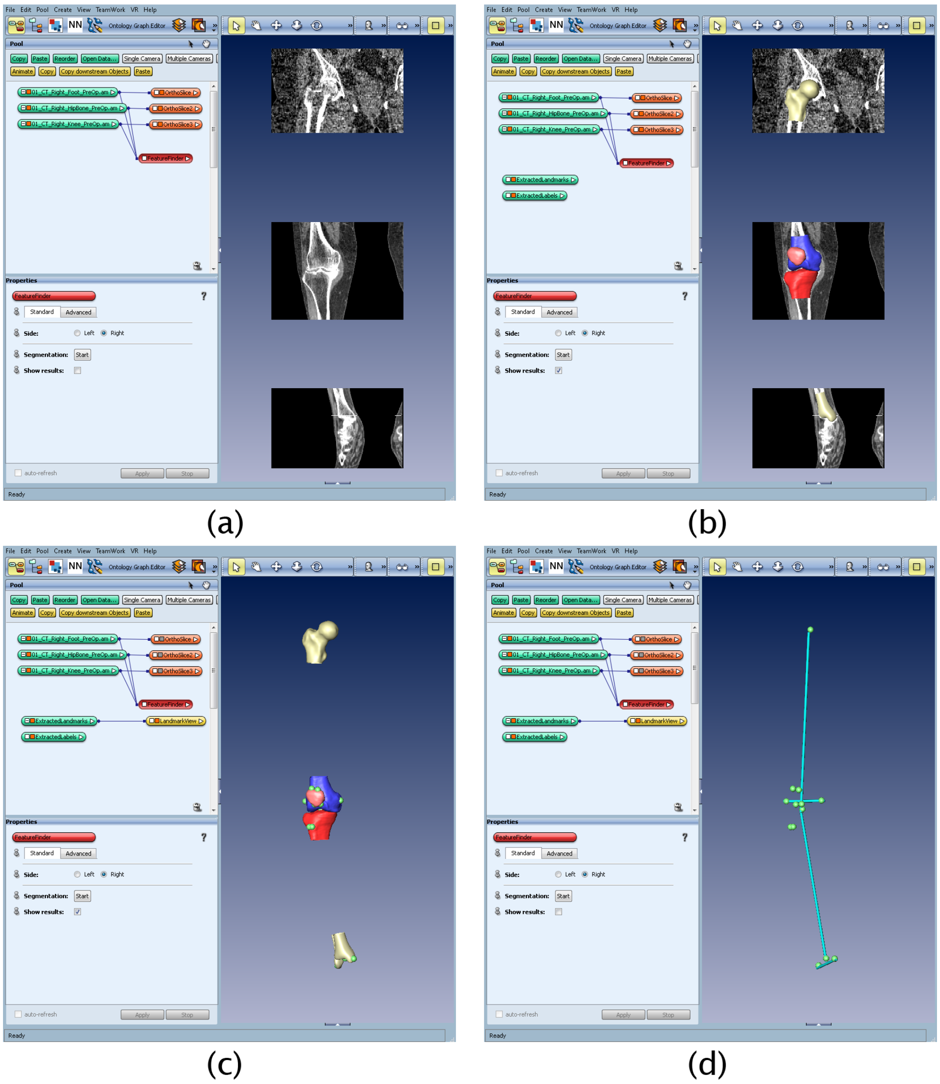

Figure 5: Our system applied to reconstruction of anatomical point landmarks of the lower limb (EU FP6 IST Project DeSSOS (027252): CT Data is loaded into ZIB-AMIRA and connected to a single module for anatomical reconstruction (red) (a), after choosing the side of the body the SSMs of the knee, femoral head and distal tibia are automatically fitted to the image data (b), based on the geometric reconstructions relevant anatomical landmarks are extracted (c), which can finally be used to extract anatomical and mechanical axes (d).