Semi-Automatic Modeling of Bones for Real-Time Surgery Support

Roger Cuypers, Benjamin Weyers and Wolfram Luther

Insititute of Computer Science and Cognitive Science, University of Duisburg-Essen
Lotharstr. 65, Duisburg, Germany

Abstract. Model-based reconstruction of human bones for surgical purposes is an upcoming field of research in informatics and kinematics. Tools for planning surgeries and real-time support require appropriate mathematical models for rendering, interacting and reconfiguration. It is our conviction that superquadrics offer this powerful mathematical modeling capability. Image-based data from MRI and X-ray examinations have to be extracted and gathered to 3D-point sets, which are afterwards fitted by superquadric-based models. The fitting process is complex and time-consuming. To solve this problem and to provide real-time simulation for surgical support, it is necessary to apply the knowledge of the expert user. This paper presents the concept and a prototypical implementation of an interactive system that involves the user in the fitting process to accelerate the calculation and enhance the resulting model.

1 Introduction

Recently, computer-based pre-operative planning has come to be considered a very important practice for giving the surgeon a detailed understanding of the complex interior body structure and the effects of possible treatment approaches. For this reason, methods and models for manipulating and processing components of the human skeletal system in an intuitive and efficient manner have become a topic of practical importance in the development of appropriate computer-based skeletal crafting and simulation tools.

One of the drawbacks of existing tools is the fact that most of them are still closely oriented towards traditional generic computer-aided construction applications that allow only simple navigation and surface manipulation using primitive geometric shapes. The resulting modeling reflects neither the topology of the bone nor the intentions of the surgeon sufficiently.

This paper presents a task-oriented, computationally efficient and flexible geometric modeling approach for a skeletal component classification, reconstruction and manipulation tool together with an effective interface that exposes the capabilities of the model to the user in an intuitive manner.

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2 Prior Research

The generation of customized geometric models from 3D point cloud data has been the subject of extensive research. In medical applications, the geometrical models were mainly selected due to their capability of giving an exact reproduction of the bone surface. Popular models are triangle meshes [8], [18] or octrees [14]. Martin et al. [12] use B-spline surfaces to model a femur's cortical and trabecular part. Kurazume et al. [9] use a statistical shape model whose parameters can be extracted from two 2D fluoroscopic images. However, feature-extraction algorithms that make use of these models receive very little beforehand-information about the global features of the bone that help them with their tasks. Furthermore, overall handling of the reconstructed models by the user is difficult due to their high number of parameters.

Of special interest are implicit superquadric (sq) models, which, due to their high modeling power and their well-behaved mathematical nature, proved a powerful tool for modeling even complex surface topologies. Originally invented by Barr in 1981, the usage and capabilities were greatly improved in papers by Solina and Metaxas by providing advanced deformation [6] and blending [16]. Zhou et al. [19] further extended the sq-model by replacing the exponents of the inside/outside function with Bezier curve functions, thus making it possible to increase surface complexity to an arbitrary level. Others tried to enhance accuracy by raising the number of components within the model.

There are several approaches that target a fully automatic generation of sq-models from scattered 3D point data. Chevalier et al. [3] introduce a split-and-merge approach to generate a composite model of several SQs. All these approaches are generic in nature and do not make use of any a priori knowledge that could improve the result leading to an optimal approximation of the actual bone surface. A sophisticated fitting approach that considers the specific bone geometries and allows basic user interaction has been studied in the context of the ongoing *PROREOP* project and is proposed in [4].

The special and complex geometric nature of the human bone requires a model-generating process to gather as much information as possible about the object of interest in order to generate an optimal result. This can best be achieved by providing the user with the ability to influence the fitting process and the parameter flow. Since the final application should be suitable for clinical environments, a comfortable user interface is mandatory. Therefore, this paper introduces a sophisticated sq-based selection tool that allows the user to intuitively steer the fitting process by helping the system identify and classify the relevant data and parameters whenever necessary.

3 Bone Modeling

The aim of our research on human skeletal modeling was to produce a geometric model of a given set of lower-limb bones that could later be used for kinematical simulation. The model should be able to reproduce the bone surface as exactly as possible while keeping the processing time short enough for real-time use. SQs offer the power to model a great variety of shapes from only a few parameters, which makes the search for appropriate parameter sets very efficient. Their dual implicit-parametric nature also allows straight-forward rendering approaches using widely available 3D programming interfaces like OpenGL.

3.1 Superquadrics

An SQ-surface is an implicit surface in 3D space that consists of all the points (x, y, z) with [1]:

$$F(x,y,z) \equiv \left(\left(\frac{x}{a_1}\right)^{\frac{2}{\varepsilon_2}} + \left(\frac{y}{a_2}\right)^{\frac{2}{\varepsilon_2}} \right)^{\frac{\varepsilon_2}{\varepsilon_1}} + \left(\frac{z}{a_3}\right)^{\frac{2}{\varepsilon_1}} = 1 \ . \qquad (1)$$

The parameters a_1, a_2 and a_3 specify the scale of the shape in x, y and z direction, and ε_1 and ε_2 define its roundness. This surface can be fitted to a 3D point cloud by minimizing a distance function that measures the proximity of the points to the surface. The distance function is defined by the radial Euclidean distance between a point and a superellipsoid, which reads as:

$$d(A, x, y, z) = F^{\varepsilon_1}(x, y, z) - 1 \ . \qquad (2)$$

where A is the surface, (x, y, z) are the points and F is the inside-outside function from formula (1) that yields 1 for points that lie on the surface, < 1 for points that lie inside and > 1 for points that lie outside the shape.

Next to the simple superellipsoidal model in Formula 1, a supertoroidal model supports toroidal shapes. Additionally, Solina [6] proposes an extended SQ model supporting tapering and bending. This allows for the modeling of a greater class of shapes, which benefits the design of bone representations introduced in the following section.

3.2 Superquadric Fitting

To fit an SQ to a set of 3D data points, it is necessary to determine a set of model parameters for which the distance between the SQ surface and the point cloud is minimized. The method used in this paper was introduced by Solina [15] and represents a least squares fit that minimizes the sum expression in Formula (3) which measures the radial euclidean distance defined according to formula (2)

$$\min_A \sqrt{a_1 a_2 a_3} \sum_{i=1}^{n} \left(F(x_i, y_i, z_i)^{\varepsilon_1} - 1 \right)^2 \ . \qquad (3)$$

where n is the number of input 3D points. This nonlinear optimization task is solved by using a sequential quadratic programming method.

In order to optimize the quality of the fit, three conditions must be met:

- The initial guess for the parameter set should already be close to the actual values; the algorithm used performs a local optimization.
- The selection of the point cloud fragment serving as input should span the target geometry as exactly as possible.
- The selection should resemble a shape that can be closely approximated by an SQ.

To achieve this goal, the semi-automatic approach introduced in this paper includes an extended selection tool that allows the user not only to define outlines that resemble simple geometrical objects, like cubes or spheres, but also to use true sq-shapes for the selection. This improves the fit, firstly, by delivering an area with an optimal sq-shape and, secondly, by providing a parameter set that represents a close initial surface approximation. The complete procedure of the interactive fit together with the user interface is described in section 4 (below).

3.3 Superquadric Bone Modeling

Fig. 1 shows implemented versions of the generic femur and hip models.

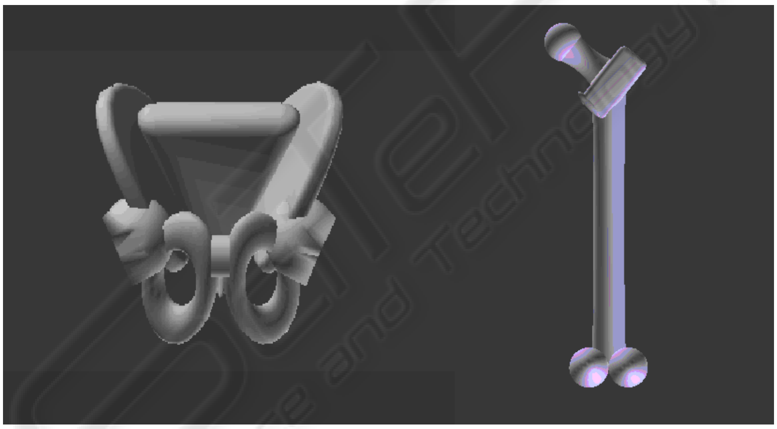

Fig. 1. Generic SQ models of hip and femur.

The bones are decomposed into several SQ primitives oriented in an analytic description of the bone shapes supplied by Goldfinger [5]. Each bone model is therefore reconstructed by fitting the SQs from the generic model to the 3D point clouds representing the respective parts of the bone. To perform this task, the significant bone parts are labeled beforehand, either by a fully automatic approach (which several tests have found unreliable) or by a semi-automatic approach, which is introduced in section 4 (below).

4 Interactive Fitting Process

In order to optimize the described fitting algorithm (section 3.2), we developed an interactive pre-fitting process, which is introduced in this section. This interactive process involves the following two major aspects:

1. The **decomposition** of a given 3D point cloud into fragments, which includes (a) the definition of point sets approximating the target geometry as exactly as possible and (b) the identification of ideal initial values for the fitting algorithm.
2. The **classification** of several parts of the geometrical model, which provides information necessary for the calculation of characteristic bone features like those listed in Table 1.

Table 1. A selection of characteristic features from the femur and hip bone.

Femur	Hip
Femur axis origin	ASIS position
Femur axis direction	PSIS position
Femur head center	Hip joint center (left, right)
Femur head diameter	Pelvis origin
Greater trochanter tip	Pelvis orientation

Fig. 2 shows how decomposition and classification are integrated in an interactive workflow. Beginning with a data cloud of 3D points, the user starts by defining subsets of points that are close to a functional fragmentation of the bone (as shown in Fig. 1 for the femur: femur head as sphere, femur shaft as cylinder etc.) and a possible model based on sq-geometries (section 3.1). To this end, we have implemented an interactive selection tool based on an sq-geometry. After finishing the decomposition, the user classifies the subsets according to the individual functions of the bone parts. This classification is comparable to a tagging operation in a tagging system [11].

After the classification step in the workflow, the user's task is to start the automatic fitting process. The fitting algorithm first extracts information from the interactive process and then calculates the sq-model for the given bone (section 3.3). From the geometric model, the characteristic values are automatically extracted and presented to the surgeon.

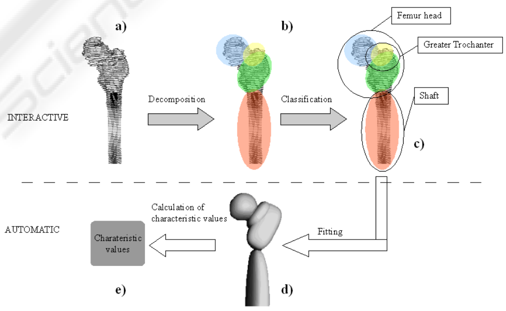

Fig. 2. Selection tool, based on the basic sq-model.

4.1 Data Decomposition

The main aim of data decomposition in the context of surgical support and modeling of bones from patient data (CRT or X-ray images) is the identification and fragmentation of the bone into its functional parts. A fully automatic approach to the identification resulted in a less precise and unsatisfying fitting result (see section 5, below). Therefore, the data decomposition in the process is a candidate for user intervention (shown in Fig. 2), resulting in a more efficient and precise fitting result.

For the manual decomposition of the initial point cloud (Fig. 2, [a]), which results from a prior segmentation process, the user interface has to offer an interactive selection tool feasible for a 3D environment. Like a spoon, the tool should separate a subset of the initial point cloud using basic drag-and-drop operations combined with transformation operations, like scaling and deforming the shape of the tool. Based on the 3D engine for mechanical multi-body modeling and simulation called *MOBILE* [7], we have developed selection tools that consist of an SQ paired with the complex dragger component of the Inventor [17] library shown in Fig. 3. This implementation combines several operations, including translation, rotation and scaling, on an sq-model that result in a tool for precise positioning and selection in a 3D point cloud. There are several reasons for using an sq-geometry in the tool. First, the geometry is closely connected to the fitting process because the result of the fitting is a bone, modeled as a set of SQs. By using SQs for selection, the fitting algorithm is initialized with an adequate SQ (see section 3, above). Second, it is easy to test whether a point in the point cloud belongs to the selected subset or not using the SQ's inside-outside function (see equation 1). Evaluating the inside/outside function which requires only few parameters is much more efficient than testing a point's position against complex surfaces like B-spline or free-form surfaces, making this tool specially suited for achieving real-time processing.

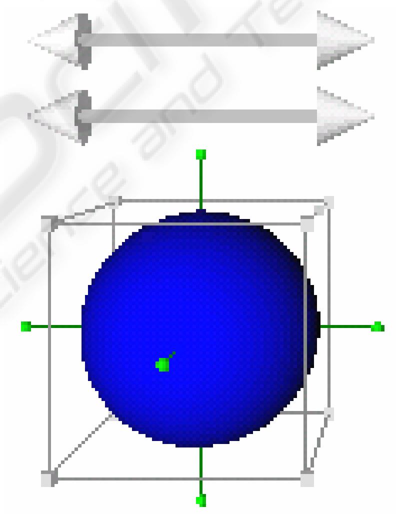

Fig. 3. Selection tool, based on the basic superquadric model.

Depending on their definition, SQs have additional parameters that influence their shapes. For the basic sq-model introduced in section 3 (see above), the parameters ε_1 and ε_2 define the roundness. Therefore, our selection tool shown in Fig. 3 offers two 3D-dragger widgets for manipulation.

For each of the two above-mentioned models, the basic one and the deformable one, an adequate selection tool has been implemented that grants access to all of the model's parameters. Each change to a parameter immediately updates the tool's shape. Due to the low complexity of the mathematical model, this update can be achieved in real-time on state-of-the-art, especially with a high-end GPU-implementation.

After selecting an area of the point cloud by having the SQ surround it, the user presses a button to create the input-subset for the fitting algorithm. The resulting information from this selection process is (a) the point-subset on which one SQ should be fitted and (b) a set of initial sq-parameters directly given by the tool itself.

This approach supersedes the automatic fragmentation of the original point cloud because of the expert knowledge of the user. It results in a faster and more precisely fitted sq-model. Fig. 2 and 3 provide a comparison of a manual measurement approach with the semi-automatic approach using the additional data described.

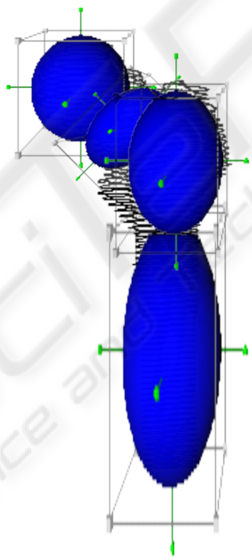

Fig. 4. Example of finished data decomposition.

4.2 Component Classification

Classification of the defined point subsets in the sq-model is closely related to the data decomposition step. After creating the subset, the user can classify the selected part of the bone by choosing an identifier out of a list (see Figure 2 [c]). This step is similar to the one used in a tagging system when the user connects data content with computer-readable semantic information (tags). Classification is mainly used (a) as additional information for the fitting algorithm and (b) to provide a subordinated calculation of the characteristic features of the bone being examined. Table 1 shows a selection of the characteristic features of a bone that can be extracted using the fitted sq-model. To do this, component classification is necessary. In the context of surgical support, it is of paramount importance that the system to be able to calculate those values automatically in order to eliminate the time overhead otherwise required for user interaction and to use mathematical models to verify accuracy. The quality of the result depends on the correct classification of every part of a given bone in the model, so that the system selects the appropriate parameter set to determine the features of the bone at hand.

4.3 Combination of Data Decomposition and Classification

Fig. 5 shows the combination of the manual data decomposition and classification operation by offering a basic bone model to the user. If the point cloud is segmented from MRI images of a leg, for example, the user has to choose the standard model of a leg. The same is true for every other bone in the human body (see Fig. 1). The classifications of all parts of the bone, like the femur head (Fig. 5), are previously connected to the single SQ in the standard model.

After loading the standard model, the user matches each SQ of the standard model to the point cloud by adjusting the parameters using the described tool (see section 4.1). In this way, data decomposition as well as component classification is combined in a unique step without changing interaction tools or paradigms.

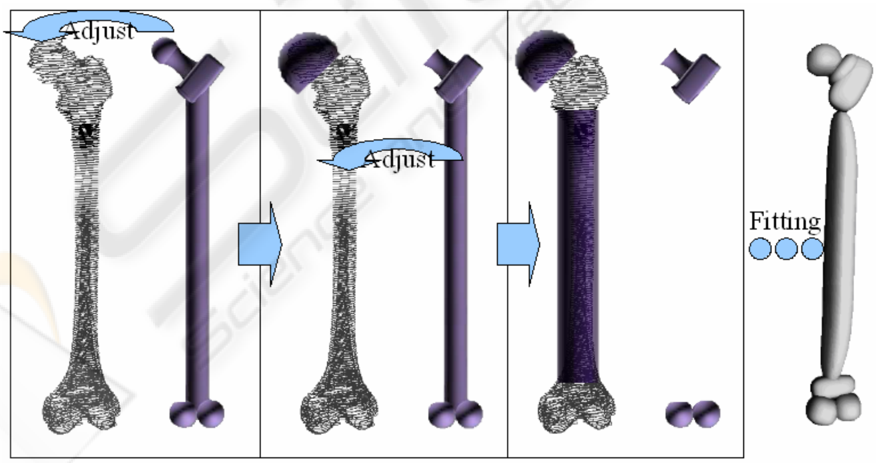

Fig. 5. One-step solution: an example of the data decomposition step for the femur.

5 Results

For testing the implementation, the decomposition and fitting procedures have been performed on five sets of intact lower-limb bone data, each taken from a human proband using MRI imaging. Each set consists of a hip bone and its two attached femoral bones. Additional validation has been performed using two sets of pig bones of the same type. Both selection tool models have been implemented and tested with the patient data as input. Due to space constrains we only list the results of two exemplary components, although the remaining result does not significantly differ. The first represents a human pelvis bone, the second an attached femoral bone. As can be seen, the absolute error between the manual and semi-automatic approaches is only a few millimeters or even less, meaning that the result comes close to established clinical standards while saving time that might otherwise be spent on user-interaction. Errors are mainly caused by ambiguities resulting from certain extreme-points lying in comparatively flat surface areas where the SQ model's approach would choose differently from the intuitive approach, yet quantitatively correctly. A fully automated test was also conducted; however, the results included components that were far from their actual position.

Table 2. Results from semi-automatic sq-fitting (femur, left, positions / lengths in m, directions as vector).

Feature	Manual method	SQ-Method
Axis	(-0,143, -0.358, -0,312)	(-0.1494, -0.3614, -0.3112)
(org / dir)	(0.1395 -0.9901 0.0068)	0.1495, -0.988, 0.0364
Head center	(-0,158 -0.12 -0.295)	(-0.1584, -0.1226, -0.2985)
Head diameter	0.044	0.0422
G.Trochanter tip position	(-0.184, -0.133 -0.347)	(-0.1812, -0.13 -0.341)
Knee axis	(-0.14, -0.565, -0.298)	(-0.138, -0.57, -0.301)
(org / dir)	(0.1013, 0.9948, 0.0001)	(0.08, 0.9967, 0.0006)

Table 3. Results from semi-automatic sq-fitting (pelvis, positions and lengths in m, directions as vector).

Feature	Manual method	SQ-Method
HJC	(-0.158 -0.12, -0.295)	(-0.158, -0.123, -0.298
(left, right)	(-0.168, -0.131, -0.113)	(-0.167, -0.132, -0.110
ASIS pos.	(-0.094, -0.06, -0.31)	(-0.096, -0.054, -0.306
(left, right)	(-0.104, -0.066, -0.088)	(-0.106, -0.051, -0.082
PSIS pos.	(-0.221, -0.051, -0.279)	(-0.22, -0.051, -0.268
(left, right)	(-0.229, -0.052, -0.132)	(-0.222 -0.055 -0.133
Pelvis origin	(-0.168, -0.131, -0.113)	(-0.167, -0.132, -0.110
Pelvis	(0.999, 0.004, 0.0445)	(0.9989, 0.004, 0.0445)
orientation	(0.0034, 0.9999, -0.013)	(-0.0034, 0.9999, -0.013)
$(\bar{x}, \bar{y}, \bar{z})$	(0.0445, 0.0134, 0.9989)	(-0.0445, 0.0133, 0.9989)

6 Conclusions

In this paper, we have presented a prototype for an interactive system that supports the surgeon in the sophisticated task of reconstructing a realistic model of the human skeletal system from 3D point data. Our technique was based on presenting the user with a powerful and efficient model to steer the reconstruction, classification and manipulation process of the algorithms. It embeds the model into an easily accessible tool that provides important information as desired to achieve an optimal result. Due to the efficiency of the sq-model and the vast possibilities of parallelization, which are discussed in [4], these techniques are suitable for real-time applications. Tables 2 and 3 show the first results using this approach in comparison with the “analogue” or “by-hand” process used during surgery planning today.

Several enhancements to the existing approach are planned. First, more analytic descriptions of a larger amount of limb components are needed to provide the user with as many templates as possible for the bone component classification task. In the longer term, it is planned to provide a model of the whole lower limb structure of the human body. Furthermore, the geometric models will be improved to allow for capturing finer topological details that result in an even more exact approximation of the bones’ surfaces. For this, the components of the sq-formula, especially those that influence overall curvature, will be brought to a more abstract level and, at the same time, be replaced by smooth interpolating functions. Finally, the selection tool will be improved in compliance with the additional capabilities of the enhanced models.

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