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3D CT Segmentation for Clinical Evaluation of Knee Prosthesis Operations

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Abstract

In surgical knee replacement, the damaged knee joint is replaced with artificial prostheses. *An accurate clinical evaluation must be carried out before applying knee prostheses to ensure optimal outcome from surgical operations and to reduce the probability of having long-term problems. Useful information can be inferred from CT scans of the knee area, that can be used to estimate the stress that will be acting on the prosthesis being implanted. This information can be exploited to tailor the prothesis to the patient's anatomy. We present some ideas for a system intended to help surgeons in evaluating the post-operative outcome of knee prosthesis implantation. We also show some preliminary results about the 3D segmentation of CT data, that is the main activity of our lab in the project.*

Categories and Subject Descriptors (according to ACM CCS): I.3.8 [Computer Graphics]: Applications

1. Introduction and Motivation

The knee joint can be severely damaged due to a variety of causes, such as arthritis or a knee injury. This can cause pain and inability to walk. In some cases, replacing parts of the joint is thus appropriate. A total knee replacement is a surgical procedure whereby the damaged knee joint is replaced with artificial shells (*prostheses*). An accurate clinical evaluation must be carried out before applying knee prostheses to ensure optimal outcome from surgical operations.

Most patients suffer from long-term problems, such as *loosening*. This occurs because either the cement crumbles or the bone melts away from the cement. In some cases, loosening can be painful and require reoperation. The results of a second operation are not as good as the first, and the risks of complication are higher.

The accurate choice of materials can improve prothesis durability. Anyway, loosening can be mainly avoided (or at least postponed) by tailoring the implanted prosthesis to the patient's anatomical peculiarities. By acquiring a CT scan of the knee area, one can infer useful information, such as posture, that can be exploited by mechanical simulators (e.g., *finite elements analysis*, FEM) to estimate the forces that will be acting on the prosthesis being implanted [PvRLR01]. This information can be exploited to estimate the lifespan of the implanted material and tailor the prothesis to the patient's anatomy.

Ollé et al. [OEHK04] presented *MedEdit*, a system that helps surgeons in operation planning and post-operative outcome evaluation. Although their system is a useful analysis and visualisation tool, it has a number of drawbacks that reduce its usability in clinical practice:

- The final model is represented as a triangle mesh, but the interior density of the bone must be known for stress estimation;
- The segmentation algorithm works on a slices slice-by-slice basis rather than using the dataset as a whole, thus reducing the chance of detecting long structures spanning over different slices;
- The segmentation requires too much interaction, since the user must set a number of seed points to initialise the algorithm and clean the resulting images from incorrectly assigned pixels;
- No error control/estimation is provided by the various sub-units of the tool.

In this paper, we present some ideas about a system that is similar in the scope to the work by Ollé et al., but aiming to overcome its limitations. Our project is a joint work of

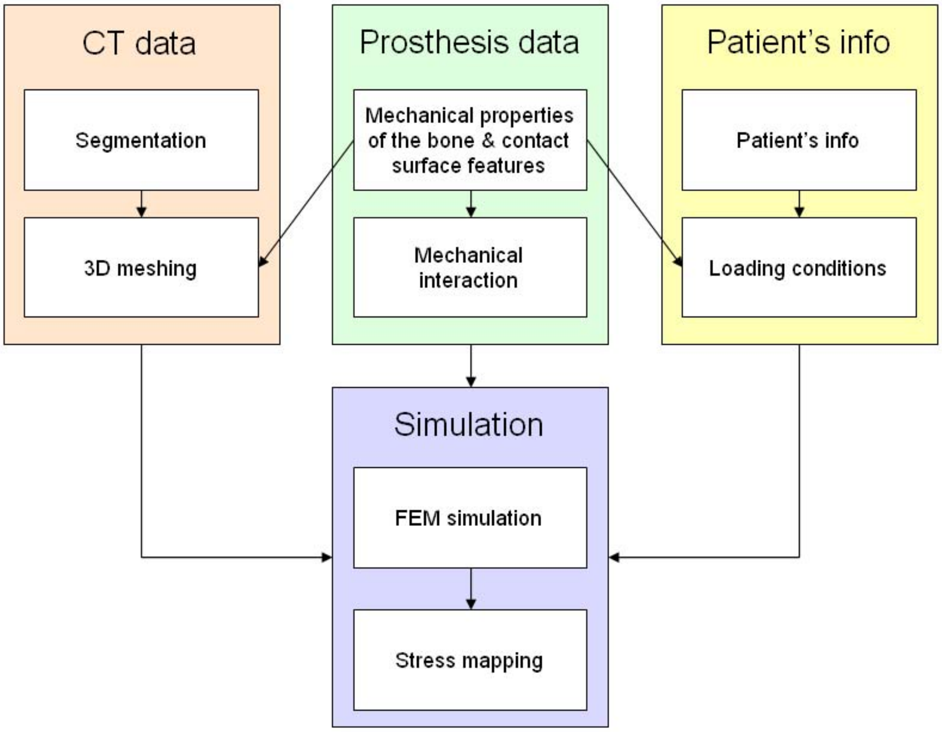


Figure 1: *Diagram of the overall system.*

a multidisciplinary team including a prosthesis production company, LIMA spa [LIM]. We also show some preliminary results about the 3D segmentation of CT data, that is the main activity of our lab in the project.

2. System Overview

Figure 1 shows a diagram of the overall system. Stress info is computed using an FEM simulation, based on the data derived from three types of analysis: meshing of knee CT data, mechanical interaction between the prosthesis and the patient's bone, and typical loading conditions for the patient's physical characteristics.

First, CT data is segmented to mark cortical and spongy bone voxels and the estimated mechanical properties of the bone are mapped on the bone voxels. A tetrahedral mesh is then extracted from the voxel model.

A mechanical model is generated to compute the interaction between bone and prosthesis surfaces, using tabulated data of the microstructure of prosthesis coating.

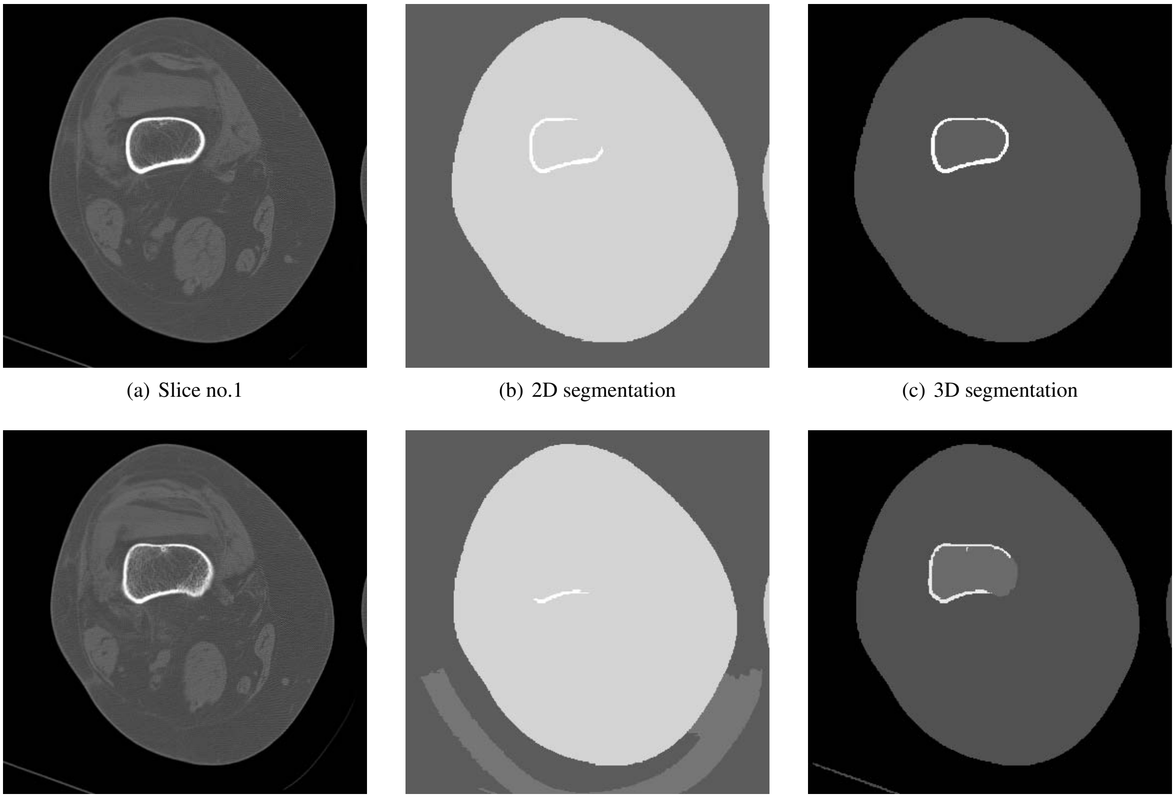
Knee loading conditions are computed from patient's info, such as sex, age, and weight, using typical static and dynamic loading conditions.

Finally, the augmented mesh model, the interaction model, and the loading conditions are used by an FEM simulator to compute a mapping of the stress that will be acting on the implanted prosthesis.

3. Segmentation of CT Data

Since the output of the system will be used for surgical planning, one of the main objectives of our research is bounding, or at least measuring, the error introduced in the various computational blocks of our system. Hence, our segmentation algorithm must give an indication on the "goodness" of the result.

CT scans are intrinsically 3D data. Most segmentation algorithms work only on 2D data, where every pixel is characterised by a vector of values in a specific colour domain [LM01,FP02]. Segmentation can be thought as a partition of a 3D space in which the third dimension is related to colour. Conversely, CT data have three spacial dimensions in which every voxel is characterised by a 12-bit scalar in the HU domain. Working on a per-slice basis, important features spanning over more slices might be undetected. Extending 2D segmentation algorithms to the 3D case poses some problems, mainly: efficiency in terms of memory and time resources, and definition of the shape of the neighbourhood of a voxel. In particular, defining the neighbourhood



(a) Slice no.1 (b) 2D segmentation (c) 3D segmentation

(d) Slice no.7 (e) 2D segmentation (f) 3D segmentation

Figure 2: *Segmentation results using the SRM algorithm and its straightforward extension to 3D data.*

of a voxel is not straightforward since voxels are elongated in the scanning direction. Most image processing algorithms assume that pixels/voxels possess a regular shape, which is not our case. Moreover, CT data of bones possess interesting statistical properties that few algorithms exploit.

Finally, user interaction should be minimised and, most of all, must be intuitive for people who do not have a Computer Science background.

To summarise, the main features of our segmentation algorithm should be:

1. Bounding/measuring the segmentation error;
2. Exploit the intrinsic structure of the 3D data by working on the whole data set, rather than on a per-slice basis;
3. Time efficiency and low memory consumption;
4. Employing a statistical model to model knee CT data;
5. Minimum and intuitive user interaction (particularly for parameter setting).

An algorithm to segment CT images of skeletal structures is presented in [KEK03]. After partitioning the CT images in void end tissue volumes, the histogram of tissue regions shows two peaks corresponding to soft tissues and bones. Exploiting these statistical features of CT scans (i.e., satisfying our fourth requirement) of bones, more accurate results are obtained.

In [NN04, NN05] an image segmentation algorithm, named *statistical region merging* (SRM), is built from sound statistical considerations. Moreover, theorems are provided to prove that (1) only *overmerging* is possible, and (2) the error with respect to the best segmentation is bounded. These features make this algorithm attractive to satisfy our first requirement. Useful considerations about *oversegmentation* in medical image segmentation [CL05] should be also taken in account.

SRM is based on a region growing technique empowered with a sound statistical test for region merging. The segmentation granularity is tuned using a single intuitive parameter, Q. This simplifies the interaction with the user, fulfilling our fifth requirement. Finally, SRM is fast since it is linear with respect to the number of pixels due to its merging strategy. Its low time complexity and memory consumption, if carefully extended to the 3D case, would satisfy our third requirement.

As a straightforward extension of the SRM algorithm to cope with 3D data, one could use a local neighbourhood including pixels belonging to neighbouring slices. Anyway, CT scans are usually made up of a large number of slices. Therefore, memory occupancy is a concern. In figure 2, we compare the segmentation results of the original (2D) SRM and of a modified version which merges the regions of three neighbouring slices. This simple extension improves the results in most cases. We expect that working on the whole dataset the results would be more robust. Unfortunately, loading the whole dataset into the main memory is unfeasible in most real cases. In order to satisfy our second requirement, we are studying a method to merge regions spanning over multiple slices, while avoiding to load the whole dataset in the main memory.

Finally, to satisfy our fourth requirement, we are trying to use statistic knowledge about the knee CT data to guide segmentation, as in [KEK03] and in [GMAn*04].

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