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Towards automatic generation of patient-specific knee models

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Abstract

The objective of the current paper is to present a pipeline designed to reduce the pre-processing time required to build subject-specific finite element knee models and facilitate their clinical integration. The pipeline involves development and validation of an atlas model of the knee joint and features of the TwInsight software suit that use novel methodologies such as: 1) deep learning for automatic segmentation of the bones from computed tomography scans, 2) automatic generation of finite element meshes with hexahedral elements, and 3) anatomical inference algorithm to adapt the atlas model to the morphology of a subject and result in the subject's personalized biomechanical model.

1 Introduction

The finite element (FE) method is a numerical method for solving physics-based problems using constitutive and governing equations. Over the past three decades, FE analysis has been used as a non-invasive approach in biomechanics to study the risk factors impacting the knee joint tissues. FE analyses normally involve three steps of pre-processing, processing and post-processing.

For a FE analysis on the knee, the pre-processing step is particularly time-consuming, as it is usually required to generate accurate subject-specific models, with detailed three-dimensional (3D) geometries and FE meshes. Therefore, its clinical implementation is facing an obstacle as the process may take several working days for each subject (Cooper et al., 2019; Rodriguez-Vila et al., 2017). However, the implementation of FE analysis can be significantly beneficial in various orthopedics related applications one of which is high tibial osteotomy (HTO) (Zheng et al., 2017).

Therefore, we have designed a pipeline that can reduce this pre-processing time for FE analyses of the knee aimed at HTO or similar purposes such as knee arthroplasties. The pipeline involves development and validation of an atlas model of the knee joint and various novel methodologies such as using deep learning for automatic segmentation, automatic generation of a volumetric mesh, and anatomical inference to adapt the atlas model to a new subject.

2 Methods

As an initial step, an atlas FE model of the knee was developed using magnetic resonance images (MRI) and CT images of a healthy subject. The tissues were reconstructed through manual segmentation in Amira software. A detailed model of the tibiofemoral joint was generated which included the femoral and tibial cartilages and menisci meshed with hexahedral elements. The anterior and posterior cruciate ligaments, medial and lateral collateral ligaments and the knee anterolateral ligament were represented by bundles of nonlinear springs. Validation steps were conducted to evaluate the design of the atlas model for the desired application before using it in the subject-specific model generation pipeline.

To be able to adapt the knee model for any new subject, a feature from the TwInsight software suit was employed that uses deep learning to automate the segmentation of bones from a CT scan. This algorithm has been trained with CT scan images along with their segmentation masks and has learned to associate the bones with their corresponding segmentations. The training has been guided by the gradient descent algorithm and the chosen neural network architecture is based on the U-Net (Ronneberger et al., 2015), which was initially designed for biomedical segmentation of 2D images, and later extended to 3D images (Çiçek et al., 2016). The performance of the trained model has been evaluated with the Dice coefficient, which is a measure of the overlap between the ground truth segmentation mask and the one generated by the algorithm.

To create the model from automatically segmented bones, an anatomical inference algorithm was used that non-linearly maps the morphology of the atlas knee model to the morphology of the subject's knee. In this process, the insertion sites of all ligament bundles are also transferred and enable us to produce the knee model from the subject without requiring additional image acquisitions than the ones used in clinical routine. Following the inference step, a fully automatic meshing algorithm was used to produce high quality hexahedral meshes of the femoral and tibial cartilages from the segmented cartilages (Rodriguez-Vila et al., 2017). A second algorithm was implemented to be used when only a priori knowledge about the contours of the cartilage surface is available. This algorithm produces hexahedral elements by normal extrusion and quality recovery using mesh relaxation.

3 Results and discussion

Pre-processing is a critical part of performing a FE analysis to assist medical interventions, and it thus requires to be adapted to a subject-specific modeling framework. The pipeline presented in this abstract successfully enabled us to significantly reduce the pre-processing time required to generate a detailed subject-specific model of the knee joint. A schematic of the developed pipeline is shown in Figure 1.

The atlas model was designed with the aim of assisting surgeons in HTO interventions. Model validation was carried out by comparing the predicted metrics of interest (intra-articular contact pressure distribution) with equivalent values found in the literature and obtained from a cadaveric study (Mootanah et al., 2014). The agreement between values merely shows that the model behaves in a realistic manner and further evaluation will be required before using our approach in a clinical setting.

A manual segmentation of a CT dataset usually takes several hours depending on the image resolution (Paz et al., 2021). The presented algorithm reduced the segmentation time for lower limb bones from 3 hours (mean segmentation time by an expert) to one and a half minutes with a Dice score of 0.96 after training with a test dataset (which included 23 scans of the lower extremity). Meanwhile, the training dataset shall be expanded to be able to capture more of the anatomical or intensity variations commonly found in medical images. The flexibility of the automatic mesh generation algorithm in terms of mesh resolution also proved it to be suitable for performing a mesh convergence analysis, thus avoiding a manual intervention which is very time consuming and requires expertise from the operator.

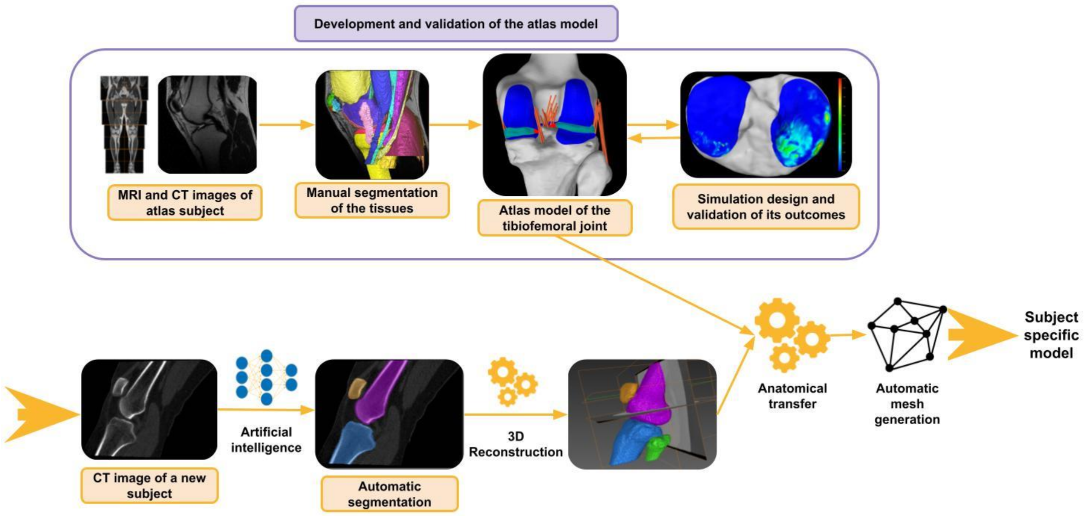

Figure 1: The TwInsight processing pipeline for automatic generation of subject-specific knee models.

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