A 3D MECHANOREGULATORY BONE HEALING MODEL COMBINING PATIENT-SPECIFIC GEOMETRY AND INDIVIDUAL LOADING DATA

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Introduction

The healing process of fractured long bones is a very complex process consisting of both biological and mechanical factors. In the last decades, simulation and modelling of bone healing have been used to understand the main mechanisms of the process, to develop implant designs and to explore specific clinical questions, cf. [3]. However, previous research on bone healing algorithms and strategies has been limited to 2D and simpler 3D geometries and has only used real patient geometry and image data prototypically, if at all. Therefore, we purposely chose real clinical data in both imaging and motion capturing as the basis in this study and combined them with currently available bone healing models.

Methods

The basis of the simulations is our established workflow consisting of model generation by segmentation of clinical imaging data combined with a musculoskeletal simulation based on the patient's motion capturing data, cf. [1]. This process allows us to perform individualized biomechanical simulations of the patient's bone-implant system, providing the macro-level information underpinning our mechanoregulatory bone healing model, cf. [2]. Based on the macroscopic mechanical stimulus, different processes can then be simulated at the cellular level (including migration, proliferation, differentiation of the different cell types) and then a new stiffness of the fracture as well as the callus area can be determined. With this new stiffness distribution, the macroscopic simulation can be performed again to get a new deformation state as new input for the mechanoregulatory healing model resulting in a loop describing a possible healing process. In our model, we have combined the different state of the art models from literature, cf. [3-6] for the inflammatory phase, the soft and hard callus phase, the biochemical signals and the blood perfusion. We then apply these models to data from a real patient and investigated the influence of different parameters and different numerical concepts on the results and their interpretation.

Results and Discussion

Figure 1 illustrates the overall framework, starting with a complex segmentation process which is manually controlled in order to get a correct callus and fracture gap. After motion capturing of the patient during a normal step forward, a musculoskeletal simulation is performed resulting in joint forces as patient-specific boundary conditions for the macroscopic simulations. The implemented healing models are currently being used to approximate the simulation results to the actual healing processes based on X-ray images through first parameter identifications. Since most models from the numerical point of view consist of coupled convection-diffusion-reaction equations and these are partially convection and/or reaction dominant, various discretization and stabilization concepts and their influence on the results must also be widely considered.

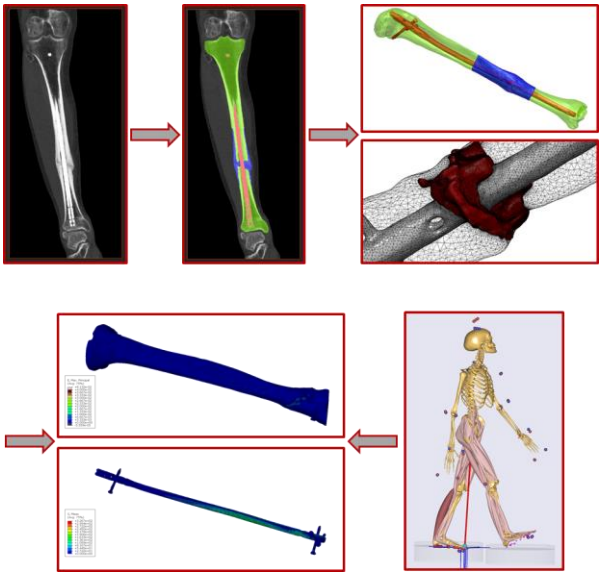

Figure 1: Illustration of our implemented workflow. Segmentation and model generation from CT data, musculoskeletal simulation based on patients' motion capture data and simulation of the mechanical stimulus in the fracture gap as basis for the mechanoregulatory bone healing model.

References

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