A LARGE SCALE OPTIMIZATION APPROACH TO GENERATE SUBJECT-SPECIFIC KNEE JOINT MODELS

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INTRODUCTION

When considering the use of computational joint models in clinical applications such as injury prevention or treatment planning, it becomes important that the model represents the joint mechanics of a specific subject [1]. While geometry of the joint structures (ligaments and articular surfaces) can be measured non-invasively by imaging techniques, this is not the case for their mechanical properties. Only indirect information is available via whole joint mechanical testing.

It has been previously shown that knee joint mechanics is relatively insensitive to cartilage load-deformation properties [2]. Ligament resting lengths, on the other hand, are a critical parameter which can not be measured from imaging data with sufficient accuracy. Here we present a novel efficient optimization method that can find model parameters for a 3D knee joint model from a large set of whole joint load-deformation measurements.

METHODS

Mechanical testing was performed on five cadaveric knee specimens using a six degree of freedom motion platform (R2000, Parallel Robotic Systems Corp., Hampton, NH) and an in-house developed software interface in LabVIEW (National Instruments Corp., Austin, TX). Tibiofemoral rotation and translation were measured in each specimen at four flexion angles (0^0, 15^0, 30^0, and 45^0) during application of internal-external moment ($\pm$5Nm in steps of 1Nm), varus-valgus moment ($\pm$10Nm in steps of 2.5Nm) and anterior-posterior drawer force ($\pm$100N in steps of 10N), a total of 192 loading conditions including 40 neutral loading conditions recorded in between the switchover from one loading direction to another.

Each specimen was imaged using MRI (OrthOne 1.0T scanner, ONI medical systems, Wilmington, MA). Computational tibiofemoral knee joint models were generated using the modeling techniques and parameters already discussed in [1]. Plastic screws were embedded in medial and lateral epicondyles of the tibia and the femur of each specimen to ensure minimal error between the coordinate systems of the experiment and the corresponding joint model. The model was implemented using existing software for 3D quasi-static joint modeling [3].

Our optimization goal was to find the 12 ligament line element resting lengths that minimize the difference between the simulated and measured tibiofemoral kinematics (3 translations and 2 rotations for each loading condition). The original joint model software [3] was designed to solve the equilibrium positions and orientations of the moving rigid bodies and particles with respect to the ground rigid body as an output. To customize the model for our optimization approach, the joint model software was accessed via the MATLAB MEX-function interface to provide the force imbalance (*GF*) of the bodies as an output for the applied external loading condition (*i*) and initial rigid body positions as an input such that,

$$C_i = GF\,(K_i) \qquad (1)$$

where K_i = model position/orientation variables for moving rigid bodies (or particles) at *i*. Analytical derivatives of *GF* with respect to K_i were obtained from the joint model [3]. The objective function that quantifies the model difference with respect to the experiments is given by:

$$f(X) = \sum_{i=1}^{n} (Si - Mi)^2 \qquad (2)$$

where $X = (K_1,\ldots,K_n,P_1,\ldots,P_m)$, P_i = unknown model parameter (resting lengths), M_i = measured kinematic variables for loading condition *i*, and S_i = corresponding kinematic variables in the model, a subset of K_i. This is a large-scale constrained optimization problem which was solved by the TOMLAB/SNOPT solver (http://tomopt.com) to minimize the objective function (2) while satisfying the constraints $C_i = 0$.

In our problem, n = number of loading conditions = 192, m = number of unknown model parameters = 12, $M_\mathrm{i} = 5$ for each loading condition i, and $K_i = C_i = 23$ for each loading condition i. This required the SNOPT algorithm to solve for (192*23) + 12 = 4428 parameters. We started the optimization with an initial guess of X where all the K_i variables satisfied the static equilibrium conditions $C_i = 0$ for an initial guess of model parameters P_i based on ligament lengths as seen in MRI scans. Results from the first specimen are presented.

RESULTS

The optimization terminated with objective function (2) having an RMS value of 3.4 mm for translations and 6.5° for rotation. Figures 1 and 2 show the model optimization results in comparison with the experimental data for selected kinematic variables. In figure 1, prominent peaks correspond to the internal-external loading conditions whereas in figure 2, the peaks can be identified in the anterior-posterior loading conditions. Kinematics are reported as femur moving with respect to tibia.

DISCUSSION

As can be seen from the figures, the model still appears stiffer than the experiments in the regions where the kinematic parameter is the primary response (peaks) to the isolated loading condition. Incorporating ligament stiffness as optimization parameter might help the model to be more accurate. The model behavior in the secondary response parameter corresponding to the isolated loading condition (e.g. anterior translation in response to rotation torque) does not appear to be in qualitative agreement with the experiments. Sensitivity analysis pointed towards ligament insertion points being responsible. With a rich multi-dimensional load-deformation dataset such as we have used, we expect it will be feasible to improve the model by including the ligament stiffness and ligament insertion points as optimizing parameters along with the ligament resting lengths.

The model optimization presented here required 10 hours of computation time. A traditional small scale unconstrained optimization in which only the ligament resting length parameters are optimized would take approximately 58 to 60 hours to reach the same level of optimality because at each parameter guess, equilibrium must be solved at all loading conditions. This introduces high computational cost and potential convergence problems.

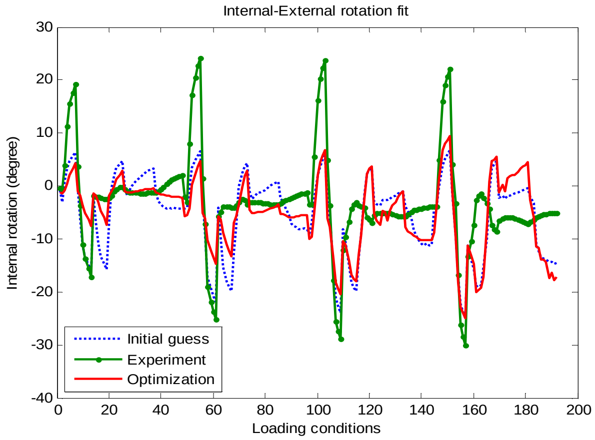

Figure 1: Comparison between the optimized model and measured Internal-External rotations.

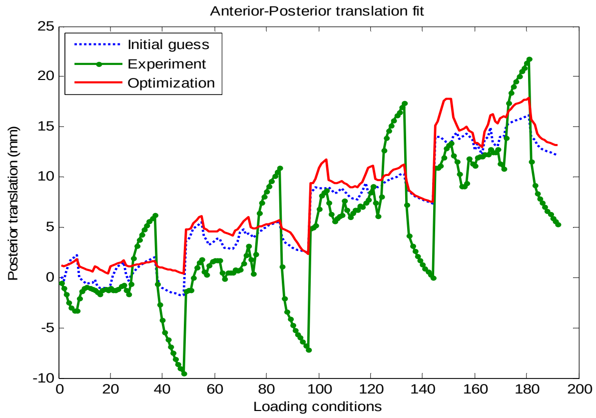

Figure 2: Comparison between the optimized model and measured Anterior-Posterior translation.

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