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DYNAMIC SIMULATION OF KNEE MOTION USING THREE-DIMENSIONAL SURROGATE CONTACT MODELING

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INTRODUCTION

Different types of computer models have been used to simulate contact conditions in human joints. One of the primary limitations of these models is computational speed. Even with simple elastic foundation (EF) contact models [1], CPU times on the order of 5 to 10 minutes for a one-cycle dynamic simulation can be prohibitively expensive for design sensitivity and optimization studies requiring thousands of simulations.

Computational limitations in other engineering disciplines have been overcome through the use of surrogate modeling. Surrogate modeling involves replacing a computationally costly model with a computationally cheap model constructed using data points sampled from the original model. Once the surrogate model is constructed, it is used in place of the computationally costly original model for subsequent engineering analyses.

Joint contact analyses pose unique challenges to traditional surrogate-based modeling approaches. The predicted contact forces are highly sensitive to the small variations in some but not all of the pose parameter inputs (i.e., three translations and rotations defining the relative position and orientation of the contacting bodies). Consequently, traditional sampling methods for constructing surrogate models produce a large number of sample points that are either out of contact or deeply penetrating.

This study proposes a novel surrogate contact modeling approach for performing 3D dynamic contact simulations of total knee replacements in a computationally efficient manner. The approach utilizes two key concepts. First, forces and torques rather than pose parameters are sampled for the sensitive degrees of freedom. Second, a “reasonable design space” approach is developed to create an efficient sample point selection process. The goal was to determine whether a dynamic simulation performed with the surrogate contact model could closely reproduce the motions and contact forces produced by an EF contact model but with substantially reduced computational cost.

METHODS

The proposed surrogate contact modeling approach was developed using a three-dimensional (3D) EF contact model of a cruciate-retaining commercial knee implant (Depuy, Warsaw, Ind) in a Stanmore simulator machine [2]. The model possessed six degrees of freedom (DOFs) relative to ground: tibial anterior-posterior translation *xt*, femoral superior-inferior translation *yt*, tibial medial-lateral translation *zt*, femoral varus-valgus rotation *xr*, tibial internal-eternal rotation *yr*, and femoral flexion-extension *zr*. Similar to a Stanmore machine, *zr* was prescribed while loads were applied for the *xt*, *zt*, and *yr* directions using ISO standard input curves [3]. Symbolic dynamics equations were derived for the femoral component and tibial insert moving with respect to ground. The equations were incorporated into a Matlab program (The Mathworks, Natick, MA) that was used to perform forward dynamic simulations with the stiff solver ode15s.

Two different contact models were used to compute the contact loads between the femoral component and tibial insert during a dynamic simulation. The first was an EF contact model employing a fine element grid of 63 x 35 on the medial and lateral sides of the tibial insert. The second was a surrogate contact model created from sample points generated by the EF contact model. The contact forces and torques, joint motions, and CPU time were compared between the two models. For both contact models, the dynamic simulation was performed on a 3 GHz Intel Xeon PC.

To develop the surrogate contact model, we needed the outputs of interest (six forces and torques) at carefully selected locations in the design space (*xt*, *yt*, *zt*, *xr*, *yr*, and *zr*). Since the net contact force and torque are highly sensitive to small changes in *yt* and *xr*, we sampled force and torque in these two sensitive directions (i.e., *Fy* and *Tx*) and motions in the remaining insensitive directions (i.e., *xt*, *zt*, *yr*, and *zr*). Specifically, we generated 5000 pairs of sample point inputs *Fy*, *Tx*, *xt*, *zt*, *yr*, and *zr* whose ranges were obtained from the EF-based dynamic simulation. Sample points were generated using the Hammersley quasirandom (HQ) sampling method, which uses an optimal design scheme for evenly distributing sample points within a multi-dimensional hypercube.

A reasonable design space (RDS) approach was employed to screen out the unreasonable sample points and obtain a more accurate surrogate model [4]. Though we can avoid physically unrealistic points by sampling *Fy* and *Tx* for the sensitive directions, some sample points can still be outside the envelope of a realistic dynamic simulation. To further refine the sample points, we used an RDS approach to screen all 5000 sample point inputs, thereby reducing the number of computational experiments to be performed with the EF contact model. First, we first performed 500 static analyses with the EF model for the first 500 HQ sample points. The outputs of each static analysis were *Fx*, *Fz*, *Ty*, *Tz*, *yt*, and *xr*. Next, we used Kriging [5] to fit *Fy* and *Tx* as a function of the 6 pose parameters, while *xt*, *zt*, *yr*, and *zr* were fitted as a function of the 6 sample point inputs. Kriging combines a polynomial trend function with a correlation function to perform multidimensional non-uniform interpolation. It has the advantage of interpolating the sample point outputs, which is appealing for deterministic computer models. After performing a cross-validation analysis, we selected a cubic polynomial and Gaussian correlation function to construct the Kriging model.

Rather than performing a static analysis with the EF model for all 5000 sample points, we used the initial Kriging model to screen all 5000 points, resulting in a reduced number of feasible sample points. Sample points were discarded if any output of the Kriging model exceeded 15% of its baseline range obtained from the EF-based dynamic simulation. After the screening process, 87% of the sample points were eliminated, leaving 675 points for constructed of an improved surrogate model. Similar to the first step, we performed 675 static analyses and the outputs were examined further to insure that all points were within the reasonable design space. The remaining 622 sample points were used to create the final Kriging models.

To calculate the contact forces and torques from 6 pose parameters during a dynamic simulation, we used the surrogate contact models to perform the following calculations. First, *Fy* and *Tx* were calculated using the 6 pose parameter inputs. Then the remaining 4 forces and torques were calculated using the pose parameter inputs *xt*, *zt*, *yr*, and *zr* and the calculated values of *Fy* and *Tx*.

RESULTS

. Dynamic simulations performed with the surrogate contact model closely reproduced the 3D motions, forces, and torques predicted with the EF contact model. The root mean square error (RMSE) and maximum absolute error (MAE) for 3D translations/rotations were less than 0.1 mm/0.3 deg and 0.3 mm/1 deg, respectively. For forces/torques, RMSE and MAE were less than 3 N/110 N-mm and 15 N/250 N-mm, respectively (Figure 1). While the dynamic simulation using the EF contact model required 17 minutes of CPU time, the same simulation performed with the surrogate contact model required less than 20 seconds.

DISCUSSION

The proposed surrogate contact model is based on two key concepts that significantly improve surrogate model accuracy and subsequent computational speed during a 3D dynamic contact simulation. First, knowledge of sensitive directions is used to generate preliminary sample points without producing physically unrealistic outputs. Second, initial Kriging models developed from a subset of the sample points are used to screen out sample points from the rest of the set that are outside the envelope of a realistic dynamic simulation. In this study, 92% (i.e., 622 out of 675) of the accepted points turned out to be within the reasonable design space. Using these two concepts, we minimized the number of static analyses required to create a surrogate contact model that reproduced dynamic simulation results from an EF contact model but at a fraction of the computational speed.

The primary benefit of using surrogate contact models in dynamic simulations is improved computational efficiency. For EF or finite element contact models, the computation time per dynamic simulation is largely determined by the number of deformable contacts in the model. Thus, a musculoskeletal computer model utilizing deformable contact models for multiple joints could easily require hours or days of CPU time to complete a single dynamic simulation. Repeated dynamic simulations as part of a sensitivity or optimization study would become impractical. For those situations, the factor of 51 reduction in computation time (i.e., 17 minutes to 20 seconds) could mean the difference between an impossible and an achievable study.

Extension of the current approach to patellofemoral and ankle joint contact analyses are topics of ongoing research. Once surrogate contact models are developed for all major lower extremity joints, it should be possible to create a full-leg musculoskeletal model incorporating multiple surrogate contact models that can be used to perform dynamic simulations in a short amount of CPU time.

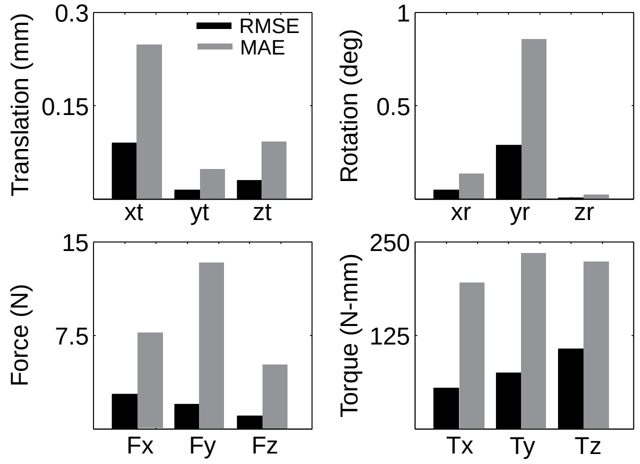

Figure 1: Comparison of motions and loads predicted by elastic foundation and surrogate contact models.

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