CAN A WELL-CALIBRATED NEUROMUSCULOSKELETAL MODEL PREDICT KNEE CONTACT FORCES ACCURATELY OVER MULTIPLE WALKING CYCLES?

Gil Serrancolí[1], Allison L. Kinney[2], Benjamin J. Fregly[3], Josep M. Font-Llagunes[1]

[1]Department of Mechanical Engineering, Universitat Politècnica de Catalunya, Barcelona, Catalonia
[2]Department of Mechanical and Aerospace Engineering, University of Dayton, Dayton (OH), USA
[3]Department of Mechanical and Aerospace Engineering, University of Florida (FL), USA
Email: gil.serrancoli@upc.edu

INTRODUCTION

Musculoskeletal models and optimization methods are often combined to estimate joint contact and muscle forces during walking. However, important model parameter values that affect estimated joint contact and muscle forces cannot be measured in the clinic. Since internal body forces also cannot be measured clinically, the ability of existing neuromusculoskeletal modeling methods to predict joint contact and muscle forces accurately during walking remains unknown.

Recently, experimental movement and imaging data collected from subjects implanted with force-measuring knee replacements have been made publicly available [1]. Using these data sets, Knee Grand Challenge competitors have developed subject-specific neuromusculoskeletal models and tested their ability to predict knee contact forces accurately over two walking cycles. Even when knee contact force data were used for model calibration, parameter values that worked well for the first walking cycle did not work well for the second one [2]. This finding indicates inaccuracies in either model parameter values, model structure, or optimization formulation.

This study used an instrumented knee data set to evaluate whether a subject-specific neuromusculoskeletal model with a single set of parameter values can predict in vivo knee contact forces accurately (< 100 N RMS error) over multiple walking cycles. The evaluation was performed using a novel two-level optimization approach that calibrated neuromusculoskeletal model parameter values with (Approach A) and without (Approach B) use of in vivo knee contact force data. The results reveal whether an existing model structure is sufficient and whether proper model calibration is necessary for generating accurate knee contact force predictions.

METHODS

Experimental data from six overground walking trials were taken from the 4th Grand Challenge Competition to Predict In Vivo Knee Loads [1]. The subject possessed an instrumented tibial prosthesis in his right leg. A subject-specific pelvis-leg model was constructed in OpenSim [3] using bone models constructed from the subject's CT scan data and implant component models taken from CAD data. The model possessed 24 DOFs and 44 muscles transferred from a scaled generic OpenSim model [4]. For all walking trials, knee kinematics (apart from flexion) were prescribed to match a single cycle of fluoroscopic data. For each walking trial, kinematics of the remaining DOFs were determined via an OpenSim inverse kinematic analysis, net joint moments via an OpenSim inverse dynamic anlysis, muscle moment arms, muscle-tendon lengths, and muscle-tendon velocities via an OpenSim muscle analysis, and leg muscle forces via a custom optimization developed in Matlab and that used a rigid-tendon Hill-type muscle-tendon model with force-length-velocity properties.

Subject-specific neural control characteristics were modeled using muscle synergy analysis concepts. For the 12 leg muscles with EMG data, activation shapes were determined by applying activation dynamics to the normalized EMG signals. Muscle synergy analysis was performed on the resulting activations to calculate five synergies (> 95% VAF), each consisting of a single time-varing neural command (NC) and an associated synergy vector containing weights that defined how the NC contributed to each muscle activation. Unique synergies were calculated for each walking trial. The NCs were applied to all muscles, including those without EMG data [5]. Consequently, predicted neural control quantities were activation scale factors for muscles with EMG data and SV weights for muscles without EMG data.

A novel two-level optimization procedure was developed to calibrate neuromuscloskeletal model parameter values with (Approach A) and wihtout (Approach B) use of the in vivo knee contact force data. Three walking trials were used for model calibration, and the remaining three trials were withheld for testing purposes.

The outer-level optimization used Matlab's non-linear least squares algorithm to adjust model parameter values (optimal fiber lengths, tendon slack lengths, moment arm offsets, activation scale factors, and synergy vector weights). The cost function minimized the weighted sum of squares of normalized passive muscle forces, activation deviations away from a synergy-based solution, reserve activations, changes in musculoskeletal model parameter values, and (for Approach A) errors in medial and lateral knee contact forces calculated from a validated regression relationship [1].

Using the current model parameter values guessed by the outer-level optimization, the inner-level optimization used Matlab's quadratic programming algorithm to perform a static optimization that minimized the sum of squares of muscle and reserve activations. Constraints were 1) equality constraints that 8 inverse dynamic loads (3 hip, 1 knee, and 2 ankle) be matched, 2) inequality constraints that the 44 muscle activations be close to the current synergy-based solution, and 3) bound constraints that all activations be between 0 and 1. *For both approaches, the inner-level optimization was identical and used no knee contact force data*.

RESULTS AND DISCUSSION

Calculated knee contact forces were much more accurate for Approach A than for Approach B (Table 1, Fig. 1). For the three calibration trials, mean RMS errors for medial and lateral knee contact forces were below 65 N for Approach A versus 285 N for Approach B. For the three test trials, mean RMS errors remained below 100 N for Approach A and below 290 N for Approach B. R^2 values were always much higher for Approach A and in both approaches were always better for medial than for lateral contact force, consistent with historical model-based predictions [1].

Differences in calculated knee contact forces between the two approaches were caused by differences in both musculoskeletal and neural control model parameter values. Differences in medial knee contact forces were caused primarily by differences in muscle optimal fiber length and tendon slack length values, while differences in lateral contact forces were caused primarily by differences in muscle moment arm offsets and activation scale factors. Mean RMS differences between the two approaches were 0.08 for muscle activations, 65.6 N for muscle forces, and 0.11 for normalized muscle lengths. The net result was that Approach B generally had higher knee muscle forces than did Approach A, leading to higher peak knee contact forces.

	Approach A	Approach B
Calibration	0.97 (57.0) 0.84 (64.2) 0.95 (110.4)	0.69 (194.6) -2.07 (284.3) 0.44 (363.9)
Prediction	0.91 (96.4) 0.76 (85.4) 0.91 (145.1)	0.68 (185.0) -1.75 (288.6) 0.44 (353.0)

Table 1. Mean R^2 values (RMS errors) for medial, lateral, and total knee contact forces produced by the two model calibration methods.

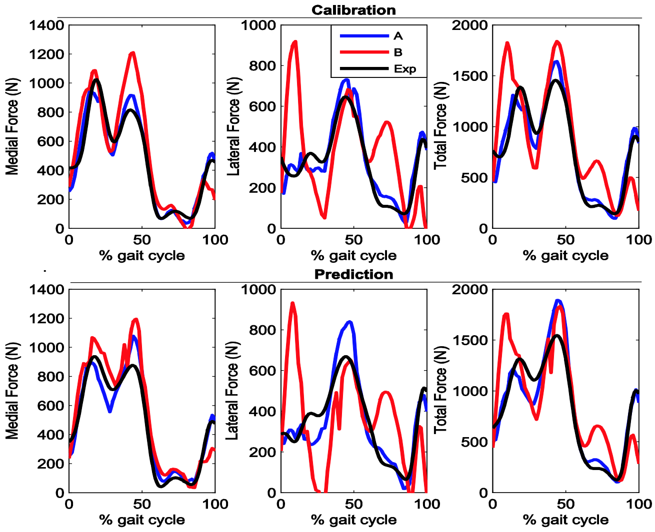

Fig 1. Knee contact forces from one calibration and one prediction trial for Approaches A and B.

CONCLUSIONS

With proper calibration, a traditional static optimization method modified to utilize subject-specific synergy controls was able to predict knee contact forces accurately (< 100 N RMS error) over six walking cycles. When the same model was calibrated without using knee contact force data, predicted knee contact forces were approximately three times less accurate. These results demonstrate that an existing neuromusculoskeletal model structure is sufficient and proper model calibration is necessary for generating accurate knee contact force predictions for walking. Future work should explore the development of improved model calibration methods.

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