The Influence of Neuromusculoskeletal Model Calibration Method on Predicted Knee Contact Forces during Walking

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Abstract

Musculoskeletal models and optimization methods are often combined to estimate joint contact and leg muscle forces during walking. However, important model parameter values, such as optimal muscle fiber lengths and tendon slack lengths, are difficult to measure *in vivo*, necessitating their calibration by other means. This study explored the influence of three model calibration methods on predicted knee contact and leg muscle forces during walking. Static optimization was used to calculate muscle activations for all three methods. Approach A used muscle-tendon model parameter values (i.e., optimal muscle fiber lengths and tendon slack lengths) taken directly from literature [1]. Approach B used a simple algorithm to calibrate muscle-tendon model parameter values such that each muscle operated within the ascending region of its normalized force-length curve. Approach C used a novel two-level optimization procedure to calibrate muscle-tendon, moment arm, and neural control model parameter values while simultaneously predicting muscle activations.

The experimental data used in this study came from the 4th Grand Challenge Competition to Predict In Vivo Knee Loads [2]. The subject was implanted with a force-measuring knee replacement in his right leg. Six normal oveground walking trials were selected for analysis. A subject-specific pelvis and lower limb model possessing 24 degrees of freedom and 44 muscles was constructed in OpenSim [3]. For each walking trial, OpenSim inverse kinematic, inverse dynamic, and muscle analyses were performed to determine muscle moment arm, muscle-tendon length and velocity, and joint moment profiles over the entire gait cycle. Activations derived from 10 processed experimental EMG signals were decomposed via synergy analysis into five time-varying neural commands (different for each gait cycle) and five sets of synergy vectors weights (the same for all gait cycles) that defined how each neural command contributed to each experimental activation.

For all three approaches, static optimization was performed for the six selected walking trials to estimate leg muscle forces that reproduced six inverse dynamic moments (3 hip, 1 knee, and 2 ankle). Reserve actuators were included to ensure that an optimal solution could be found, and the problem formulations were identical apart from additional inequality constraints for Approach C. For Approaches A and B, static optimization was performed for each of the six walking trials separately. For Approach C, static optimization was performed for three calibration walking trials simultaneously as the inner level of a novel two-level optimization procedure. The goal of the two-level optimization was for the outer level to find model parameter values that would cause the inner level to predict the correct medial and lateral knee contact forces without having knowledge of them. To this end, the outer level optimization adjusted muscle-tendon, moment arm, and neural control model parameter values and passed them to the inner-level static optimization. Neural control model parameters consisted of activation scale factors for muscles with associated EMG data and synergy vector weights for muscles without associated EMG data. The outer-level cost function tracked experimental medial and lateral knee contact forces, tracked activations constructed from a linear combination of experimental neural commands, and minimized passive muscle forces, reserve activations, and changes in model parameter values, while the inner-level cost function minimized muscle and reserve activations. The inner-level also included equality constraints to match the six inverse dynamic loads, inequalty constraints to cause predicted activation shapes to be close to a linear combination of experimental neural commands, and bound constraints to limit activations to remain between 0.01 and 0.7. For the three walking trials held back for evaluating the calibrated model, only the inner-level optimization was run to predict medial and lateral knee contact forces.

For both calibration and prediction trials, Approach C reproduced the experimental medial and lateral knee contact forces closely (Table 1, Figure 1), Approach B predicted medial contact forces reasonably well but lateral contact forces poorly [4], and Approach A predicted contact forces poorly for both compartments, often producing infeasible solutions. Differences in model parameter values for five key muscles accounted for most of the difference in knee contact forces predicted by Approaches B and C. This finding suggests that calibrating the model with other type of movement trials where these muscles play a more important role could improve the calibration process.

The main conclusions from this study are three-fold. First, poor calibration of neuromusculoskeletal model parameter values may be a primary contributing factor to inaccurate prediction of knee contact (and by implication, leg muscle) forces during walking. Second, researchers should ensure that muscles operate on the ascending regions of their normalized force-length curves during walking. Third, additional research is needed to determine how model parameter values should be calibrated to obtain accurate lateral as well as medial knee contact force predictions when experimental contact force data are not available.

Table 1. Mean R^2 values (and RMSE) for knee contact forces (medial, lateral, and total) relative to *in vivo* measurements as produced by Approaches B and C. Approach A predictions were unrealistic.

	Approach B	Approach C
Calibration	0.91 (99.5), -2.30 (290.2), 0.56 (323.9)	0.97 (57.0), 0.84 (64.2), 0.95 (110.4)
Prediction	0.89 (107.1), -1.77 (296.5), 0.63 (286.3)	0.91 (96.4), 0.76 (85.4), 0.91 (145.1)

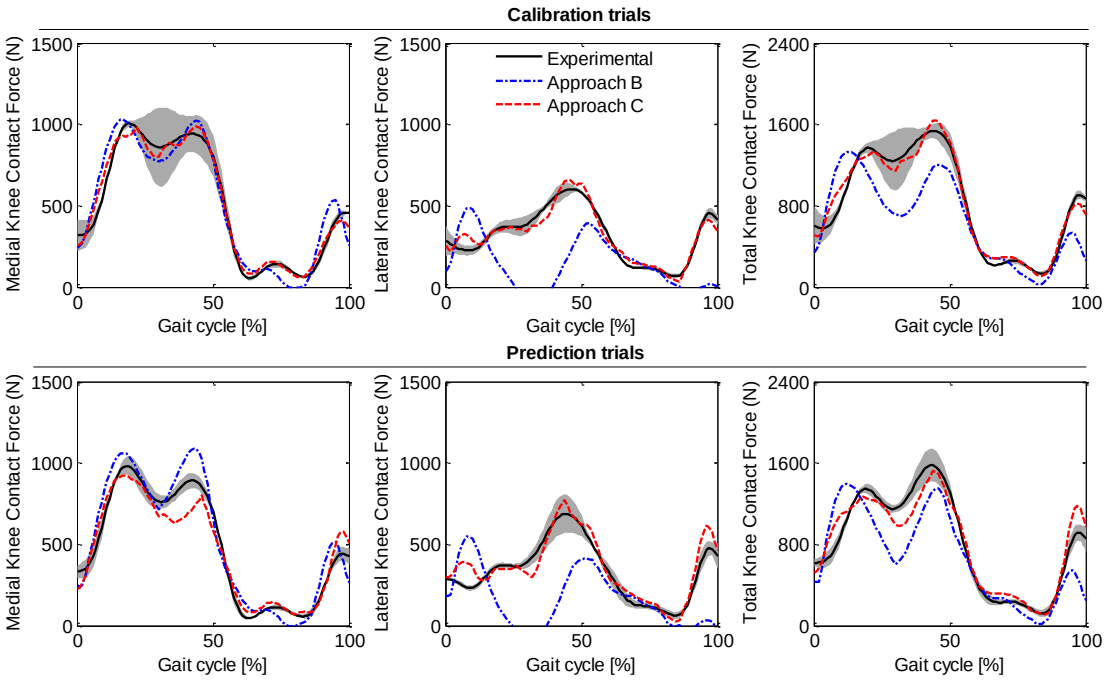

Figure 1. Mean knee contact forces for calibration (top row) and prediction (bottom row) trials relative to *in vivo* measurements (black line, two standard deviations represented by gray bands) as produced by Approach B (blue curves) and Approach C (red curves).

References

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