OPTIMIZATION PROBLEM FORMULATION FOR PREDICTING KNEE MUSCLE AND CONTACT FORCES DURING GAIT

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INTRODUCTION

The human body has more muscles than degrees of freedom (DOF), which leads to indeterminacy in the muscle force calculation. In this study, an optimization problem to estimate the lower-limb muscle forces during a gait cycle of a patient wearing an instrumented knee prosthesis is formulated. It consists of simulating muscle excitations in a physiological way while muscle parameters are calibrated.

Two different approaches are considered. In Approach A, measured contact forces are applied to the model and all inverse dynamics loads are matched in order to get more accuracy on muscle parameter calibration. In Approach B, only the inverse dynamics loads that are not affected by the knee contact loads are matched. Using this approach, contact forces can be predicted and validated by comparison with the experimental ones. The latter approach is a test of the optimization method and it can be used for the cases that no knee contact forces are available.

METHODS

The experimental data used in this study are from the fourth Grand Challenge Competition to Predict In Vivo Knee Loads [1], which are available online. The patient was an 88 year old male implanted with an instrumented knee replacement in his right leg. Muscle forces were estimated for one normal gait trial.

A patient-specific model of the subject's leg (pelvis through toes) was used to calculate joint loads and muscle moment arms (Fig. 1). The model was developed using OpenSim 3.0 [2] and consists of six joints: pelvis (6 DOF), hip (3 DOF), knee (6 DOF), patellofemoral joint (6 DOF), ankle (2 DOF) and metatarsalphalangeal joint (1 DOF). The knee implant was modeled using the subject's tibial tray and femoral component attached with a weld joint to the tibia and femur, respectively. The model had 44 muscles with ligaments being neglected.

Fluoroscopy and implant contact force data were used to generate dynamically consistent knee motion data. This task was achieved using pose optimization of an elastic foundation contact model of the subject's implant components [3]. The optimized knee motion was input to an OpenSim inverse kinematics analysis that determined the hip (3 DOFs), knee flexion, and ankle (2 DOF) angles that best matched experimental marker data for the selected gait trial.

An inverse dynamics optimization approach was developed to predict muscle forces consistent with all available experimental data, including inverse dynamics loads (3 hip, 3 or 1 knee, and 2 ankle) calculated from experimental marker and ground reaction data, knee kinematics determined from fluoroscopic data, muscle EMG curves, and instrumented implant forces and torques.

Two categories of optimization problems were formulated. The first (Approach A) matched 3 inverse dynamics knee loads (superior-inferior force, adduction-abduction moment, and flexion-extension moment) and applied the experimental knee contact forces and torques directly to the tibial tray and femoral component. The goal was to verify that the formulation could match all available experimental data while producing physiologically realistic muscle forces. The second category (Approach B) matched only 1 inverse dynamics knee load (flexion-extension moment) and did not apply the experimental knee contact forces and torques to the model. The goal here was to evaluate prediction of medial and lateral knee contact force when knee contact force data are not available.

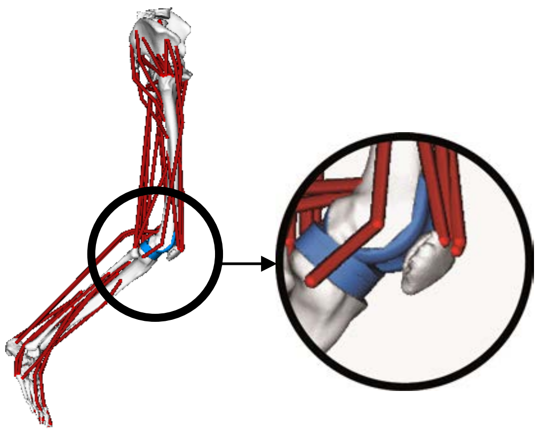

Fig. 1: Musculoskeletal lower-limb model.

For both approaches, muscle-tendon model parameter values were calibrated as part of the muscle force prediction process. Parameter values that were calibrated include: optimal muscle length l_{01}^M, tendon slack length l_s^T, peak isometric force F_0^M, and activation and deactivation time constants τ^{act} and τ^{deact}. Both approaches also adjusted B-spline nodes defining the shapes of the muscle excitation curves in the model.

The optimization problems were solved using MATLAB's Levenberg-Marquardt non-linear least squares algorithm (The Mathworks Inc., Natick, MA). The cost function included terms that tracked experimental data (inverse dynamics loads and EMG curves normalized to 1), tracked uniformly scaled muscle-tendon model parameter values, and bounded errors in muscle excitation, normalized muscles lengths, and normalized muscle velocities. Each term in the cost function was represented as

$$f = \left(\frac{1}{r} \left(x_s - x_k \right) \Big/ x_k \right)^{\exp} \quad (1)$$

where x_s is a design variable, x_k is the value to match, r is the allowable variation in the variable, and exp is the exponent. Tracking terms were given an exponent of 2, while bounds terms were given an exponent of 10. The cost function also included additional terms to minimize excitations squared only for muscles without EMG data (Approaches A1 and B) or for all muscles (Approach A2).

RESULTS AND DISCUSSION

Approaches A1 and A2 were able to track all 8 inverse dynamics loads (and thus medial and lateral knee contact forces) and the majority of muscle EMG shapes closely (Tables 1 & 2). These approaches produced physiologically realistic values for normalized muscle lengths and shortening velocities and muscle-tendon parameter values that remained close to uniformly scaled literature values. However, when excitations were minimized for muscles with experimental EMG data (Approach A2), some muscle excitations were driven close to zero, which was not physiological. Approach B was also able to track 6 inverse dynamics loads closely and an even larger number of muscle EMG shapes closely while producing physiologically realistic muscle forces with parameter values closed to scaled literature values (Tables 1 & 2). However, prediction of the two omitted inverse dynamics loads at the knee was poor, leading to over-prediction of medial and lateral knee contact forces despite minimization of excitations for muscles without EMG data (Fig. 2).

Approach	Knee sup force	Knee flex moment	Knee add moment	Ankle flex moment	Ankle inv moment	Hip flex moment	Hip add moment	Hip rot moment
A1	0.97	1	0.89	1	1	1	1	0.98
A2	0.97	1	0.89	1	1	1	1	0.98
B	-2.3	1	-1.9	1	1	1	1	0.98

Table 1: R^2 values for inverse dynamics loads.

	$R^2 \geq 0.75$	$0.25 \leq R^2 \leq 0.75$	$R^2 < 0.25$
A1	14	5	6
A2	16	4	4
B	20	1	3

Table 2: No. of EMG signals within specified R^2 ranges.

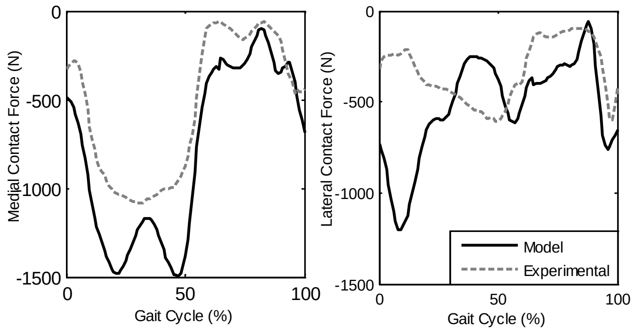

Fig. 2: Predicted medial and lateral contact forces for optimization Approach B.

CONCLUSIONS

Overall, this optimization problem formulation was able to match all experimental data well when three inverse dynamics knee loads were included in the problem formulation and experimental knee contact forces were applied to the model. Poor knee contact force prediction when two inverse dynamics knee loads were removed suggests an inadequate cost function or missing elements from the model. EMG tracking with simultaneous minimization of all muscle excitations did not work well, suggesting that a consistent method is needed for handling muscles without and with experimental EMG data (e.g., excitations constructed from experimentally calculated muscle synergies). Knee contact forces contributed significantly to the knee flexion-extension moment during stance phase, suggesting that a moving flexion-extension axis may be needed to produce proper contact force predictions.

REFERENCES

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