Formulation to predict lower limb muscle forces during gait

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Introduction

The human body has more muscles than Degrees of Freedom (DoF), and that leads to indeterminacy in the muscle force calculation. This study proposes the formulation of an optimization problem to estimate the lower-limb muscle forces during a gait cycle of a patient wearing an instrumented knee prosthesis. The originality of that formulation consists of simulating muscle excitations in a physiological way while muscle parameters are calibrated. Two approaches have been considered. In Approach A, measured contact forces are applied to the model and all inverse dynamics loads are matched in order to get a physiological calibration of muscle parameters. In Approach B, only the inverse dynamics loads not affected by the knee contact loads are matched. With that approach, contact forces can be predicted and validated by comparison with the experimental ones. Approach B is a test of the optimization method and it can be used for cases where no knee contact forces are available.

Materials and methods

The experimental data used in this study have been extracted from the fourth Grand Challenge Competition to Predict In Vivo Knee Loads[1], and are available online. They corresponded to an 88 year old male implanted with an instrumented knee replacement in his right leg. The 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 the joint loads through an inverse dynamics analysis in OpenSim 3.0[2] using available kinematic and dynamic data. Fluoroscopy and implant contact force data were used to generate dynamically consistent knee motion data.

The developed algorithm optimizes the simulated EMG signals and muscle parameters (optimal muscle length l_{01}^{M}, tendon slack length l_{s}^{T}, peak isometric muscle force F_{0}^{M}, and activation and deactivation time constants τ^{act} and τ^{deact}) to match the simulated joint loads with those obtained from the inverse dynamics analysis, and to match the simulated EMG with the experimental. In Approach A, the inverse dynamics loads to be matched are the following: the 3 hip moments (flexion, adduction and rotation), 3 knee loads (flexion and adduction moment and inferior-superior force) and the 2 ankle moments (flexion and rotation). In Approach B, the same loads are matched except for the knee adduction moment and the inferior-superior force, considered to be affected by the knee contact forces.

In both approaches, the optimization problem is 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.

Results and discussion

R^2 values for the match of inverse dynamic loads and EMG shapes are presented in Tables 1 and 2. Approach A was able to track all 8 inverse dynamics loads (and thus medial and lateral knee contact forces) and the majority of muscle EMG shapes closely. This approach produced physiologically realistic values for normalized muscle lengths and shortening velocities and muscle-tendon parameter values that remained close to uniformly scaled literature values. Approach B was also able to track closely 6 inverse dynamics loads and an even larger number of muscle EMG shapes while producing physiologically realistic muscle forces with parameter values close to scaled literature values. 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.

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

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
A	0.97	1	0.89	1	1	1	1	0.98
B	-2.3	1	-1.9	1	1	1	1	0.98

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

	$R^2 \geq 0.75$	$0.25 \leq R^2 \leq 0.75$	$R^2 < 0.25$
A	16	4	4
B	20	1	3

Conclusion

Overall, this optimization problem formulation was able to match successfully all experimental data 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 that the problem constraints need to be improved.

References

[1] Fregly BJ *et al.*, J Orthop Res. 30: 503-513, 2012.
[2] Delp SL *et al.*, IEEE T Bio-Med Eng. 54: 1940-50, 2007.