Including hamstrings and vasti EMG improves knee joint compressive force estimations from musculoskeletal modeling

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Summary

Altered muscle coordination strategies in knee osteoarthritis (OA) patients can be one cause of increased knee joint loading. This study estimated knee joint forces using an electromyography (EMG)- informed musculoskeletal (MSK) model with minimal EMG inputs. Our approach can accurately predict the peak compressive forces in the knee joint during walking using hamstring and vasti EMGs as inputs. This result can be relevant for monitoring joint loading in daily life.

Introduction

The onset and progression of degenerative joint diseases such as knee OA has been associated with abnormal joint mechanics. Altered muscle coordination strategies, e.g. muscle co-contraction, can cause increased knee joint loading [1]. EMG-informed MSK models can estimate joint loading while accounting for patient-specific muscle coordination strategies [2]. Despite this understanding, there is currently a lack of effective treatments in the early stages of OA that consider patient-specific joint loading. Monitoring changes in joint loading in OA patients during their daily lives can enable us to individualize treatment. However, a practical approach requires minimal measurement and model setup without initial model calibration. The MSK modelling study aims to estimate knee joint loading using a minimal set of EMGs considering patient-specific muscle coordination strategy.

Methods

The experimental data were obtained from the CAMS dataset [3]. For the MSK model, a generic full-body model was scaled to the subject's anthropometry [4]. Inverse kinematics was performed to estimate the joint angles during walking. Then, joint angles, ground reaction forces, and EMG measurements were given as input to the rapid muscle redundancy (RMR) solver to predict muscle activations and knee joint forces [5]. The current RMR solver's cost function computes muscle activations **a** and controls **c** by minimizing weighted-squared activations at each timestep. The term **e** was added to the cost function to reduce the difference between predicted and measured muscle activation. The adapted cost function is defined as:

$$J(a,c,e) = \sum_{i=1}^{N_m} w_i a_i^2 + \sum_{j=1}^{N_q} v_J c_j^2 + \sum_{l=1}^{N_r} u_l e_l^2 \qquad (1)$$

, where *wi*, *ul*, and *vj* are weightings to encourage the use of muscles and minimize deviation of muscle activations over reserve actuators. Thus, we set them to 1, 3, and 10, respectively.

Results and Discussion

The peak compressive forces of the EMG-informed simulations at 45% of the gait cycle show good agreement with the in vivo measurements (Figure 1). Static optimization (SO) and RMR solver underestimate the peak compressive knee forces as they don't account for the subject's muscle co-contraction. Furthermore, the RMR solver takes passive muscle forces into account and predicts lower peak compressive forces compared to the SO solver.

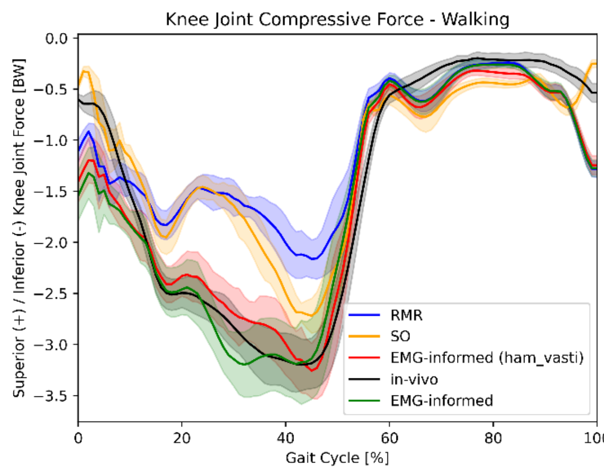

Figure 1: Predicted compressive knee joint forces during walking of the RMR (blue), SO (orange), EMG-informed (hamstrings and vasti) RMR (red), and EMG-informed (all 16 measured muscles) RMR (green) solver compared to the in-vivo measurements (grey).

Conclusions

The EMG measurements of hamstrings and vasti as inputs for the EMG-informed MSK simulation were sufficient to accurately predict this subject's peak compressive forces in the knee joint. This result is highly relevant when monitoring joint loading in daily life with only a minimal set of EMGs available.

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References

[1] Febrer-Nafría M et al. (2023). *J Biomech*, **161**: 111851.
[2] Pizzolato C et al. (2015). *J Biomech*, **48**: 3929-36.
[3] Taylor WR et al. (2017). *J Biomech*, **65**: 32-9.
[4] Uhlrich SD et al. (2022). *Scientific Reports*, **12**: 9842.
[5] Belli et al. (2023). *PLoS One*, **18**: e0295003.