Rapid Calibration of Electromyogram-Informed Neuromusculoskeletal Models Using Differentiable Physics.

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Summary

Electromyography (EMG)-informed neuromusculoskeletal (NMS) models predict individual-specific muscle and joint forces, but their accuracy depends on parameter calibration, which is typically slow. This study introduces a differentiable physics framework to reduce calibration time. We developed an auto-differentiable Hill-type muscle model and applied a gradient-descent optimization to calibrate model parameters. The method was validated using upper-limb data, comparing the new approach to a commonly used simulated annealing method. Calibration time was reduced by 13-fold without compromising prediction accuracy. This rapid calibration method enables real-time applications and integration with neural networks, facilitating advancements in personalized rehabilitation and biomechanical analysis.

Introduction

EMG-informed NMS models predict physiologically valid individualized muscle and joint contact forces. However, the accuracy depends on the model's neuromuscular parameters (e.g., optimal fiber length, tendon slack length) that vary across individuals, and are not easily measured. Calibration of NMS model parameters is required to minimize error between model predictions and experimental data [1]. However, NMS model calibration uses optimization that converges slowly (hours), limiting deployment in time-critical applications.

Substantial reduction in calibration time may be possible with differentiable physics. This combines physics-based modeling with backpropagation using automatic differentiation for efficient gradient-descent optimization [2]. We implemented an EMG-informed NMS model in this differentiable physics framework and evaluated its reduced calibration time while producing physiologically valid predictions.

Methods

We developed an auto-differentiable Hill-type muscle model with an elastic tendon in LibTorch, and implemented it as a calibration method in CEINMS [1]. The reformulated model enabled backpropagation to calculate gradients of the loss with respect to each model parameter. For this calibration, the AdamW optimizer was used to adjust the model parameters.

Upper-limb EMG and marker data from one participant [3] were processed using OpenSim, estimating joint moments, musculotendon lengths, and moment arms. An uncalibrated NMS model containing three degrees of freedom (shoulder abduction and rotation, and elbow flexion) and 16 muscles was constructed from the linearly scaled OpenSim model.

The differentiable physics calibration was compared to the simulated annealing calibration currently implemented in CEINMS. Both calibrations were performed across the same three trials, adjusting optimal fiber length, tendon slack length, strength coefficient and three activation dynamics parameters. The loss function minimized error between predicted and experimental joint moments (from inverse dynamics), while penalizing non-physiologically valid solutions. After each calibration type, the models were executed in CEINMS EMG-driven mode [1] on the same trials that were not used within the calibration. Predicted and experimental joint moments were compared using root mean squared error (RMSE) and coefficient of determination (R^2).

Results and Discussion

The differentiable physics method achieved moment tracking accuracy comparable to the CEINMS approach (Figure 1), but calibration time decreased from 40 to 3 minutes, a 13-fold speedup. This new formulation enables rapid calibration for deployment in time-sensitive applications, including real-time biomechanical analyses and personalized rehabilitation.

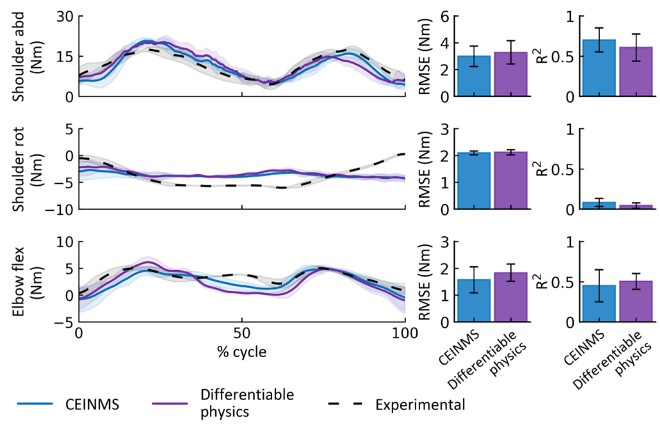

Figure 1: Moment tracking for calibrated models across all cycles.

Conclusions

An auto-differentiable Hill-type model with gradient-descent optimization reduced NMS model calibration time. This differentiable physics approach is seamlessly compatible with neural network methods, facilitating future implementation of hybrid physics-informed neural networks for NMS modeling.

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