Neural Networks Can Reduce Barriers to Personalized Musculoskeletal Models: A Study of Tasks in the Hand

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Summary

Current methods for personalizing musculoskeletal models require extensive experimental data and processing. Here, we demonstrate that musculoskeletal hand models personalized using only lateral pinch force data and a custom neural network can result in task generalization and low errors. Specifically, neural network personalized hand models had significantly lower errors when predicting muscle activation compared to other state-of-the-art personalization methods.

Introduction

Personalizing musculoskeletal models to improve model predictions often requires considerable experimental data [1]. Scaling is the most basic form of personalization and uses anthropometrics to adjust the length and mass of modeled segments. Since scaling is limited to length and mass, parameter optimization can be used to further personalize models. For example, the Neuromusculoskeletal Modeling Pipeline (NMSM) uses a common form of optimization in which a scaled model's parameters are tuned by minimizing the error between the predicted joint moments of an electromyography (EMG) driven forwards simulation and the predicted joint moments from an inverse simulation [2]. However, optimization-based personalization methods are time-consuming in terms of the time to collect, process, and leverage experimental data. To overcome this barrier, we have developed a neural network (NN) that can estimate parameters for personalized hand models using only force data from a simple lateral pinch task [3]. The NN reduces the need for experimental data, as it is trained with simulated data. Here, we evaluate the performance of NN personalized models compared to optimization-based personalization methods.

Methods

Preliminary analysis on 11 participants [age 42.1 ± 21 years; 4 male, 7 female] was performed for this IRB-approved study. Briefly, each participant performed 5 trials of 15 tasks [7 range of motion (RoM); 4 isometric at 100% & 50% effort], while fine-wire EMG (8 thumb muscles), motion capture (44 markers), and six-DOF forces were recorded.

For each participant, 12 different musculoskeletal models were created in OpenSim 4.4. The generic model consisted of the MoBL-ARMS upper limb and ARMS hand and wrist models [4,5]. The scaled model was generated from static marker data. Five models were created with NMSM by tuning with either 50% MVC, 100% MVC, all isometric, all RoM, or all collected tasks. NMSM models were tuned using 2 randomly selected trials per task, with remaining trials used for evaluation [1]. Five models were made with the NN by using each pinch trial separately to predict parameter sets.

Model performance was evaluated using measured kinematics as inputs to static optimization to predict muscle activations. Root mean squared error (RMSE) was calculated between measured EMG and predicted activations. Repeated-measures ANOVA and post-hoc comparisons determined significance.

Results and Discussion

NN personalized models had significantly ($p < 0.05$) lower RMSE across 9 of 15 tasks compared to other models (Fig. 1). Across all tasks, the average NN model had the lowest RMSE for 7 of 8 muscles. In contrast, NMSM models had significant differences from generic and scaled models for 5 muscles. Interestingly, scaled models had the highest RMSE, which may reflect that scaling in OpenSim does not automatically adjust maximum isometric force or pennation angle. The improved performance of the NN personalized models was not limited to the lateral pinch task used to train the network. This indicates NN personalized models can be generalizable, meaning they do not require task dependent personalization. The NN was also efficient taking 0.6 seconds per participant, while NMSM required 52 hours of data processing time per participant. Despite significant findings, high variance existed across participants. High variance is expected as the study age range (21 to 74 years) is large and muscle redundancy causes the solution space to be semi-infinite for inverse simulations.

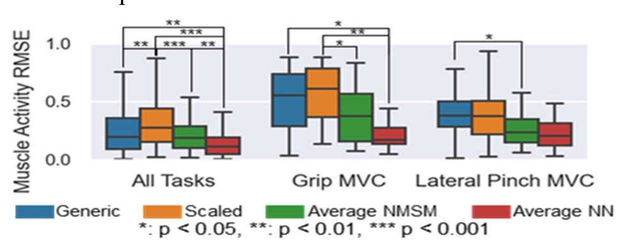

Figure 1: Model performance for 1 representative muscle (*flexor pollicis longus*) and 3 representative tasks. Note, the 5 NMSM and 5 NN models are displayed as averages to enhance readability.

Conclusions

Our work suggests that musculoskeletal hand models personalized with neural networks are equivalent to current methods that require more experimental data.

Acknowledgments

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