Learning from the Measurable: Predicting Changes in Hill-Type Muscle Parameters from Lateral Pinch

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Summary

Musculoskeletal models enable subject-specific analyses through controlled variation of biomechanical parameters. However, modeling even simple tasks requires assumptions about unmeasurable Hill-type muscle parameters. We tested an approach to estimate these parameters from simulated lateral pinch force using artificial neural networks. Our results suggest classifying muscle parameters from pinch force is feasible, but complex models may require more input features.

Introduction

Musculoskeletal models of the thumb are defined by over 109 independent biomechanical parameters [1]. Many of these parameters are difficult or impossible to measure *in vivo*, hindering development of subject-specific models. In this study, we present a data-driven approach to estimate the maximum isometric muscle force (unmeasurable parameter) from pinch force (measurable clinical outcome). Leveraging forward dynamic simulations and artificial neural networks (ANNs), we elucidate the role maximum isometric force of extrinsic muscles plays in lateral pinch force generation.

Methods

Four datasets of lateral pinch force were produced via forward dynamics in OpenSim v 3.3 [2]. A thumb model [1] was varied by adjusting maximum isometric force of the extrinsic thumb muscles [*abductor* (APL), flexor (FPL), and extensor (EPL) *pollicis longus* and *extensor pollicis brevis* (EPB)]. Datasets 1 through 4 contained 120, 1024, 3197, and 4096 simulations as 1-4 muscles were adjusted, respectively. The output of each simulation was a three-component pinch force vector versus time. The time-series force data was separately input into 2 ANNs: *feedforward* and *long short-term memory* (LSTM). Feedforward ANNs lack feedback within the structure [3], but are less computationally costly. LSTMs have feedback and thereby "memory" [4], which can aid study of time-dependent activities. Each ANN included 4 input nodes (time and three-component force vectors), 4 hidden nodes, and 1 hidden layer. Labeled data were grouped by whether the varied muscles were above ("High") or below ("Low") mean maximum isometric force. Modifying more muscles resulted in more labeled groups, requiring 2, 4, 8, or 16 output nodes for Datasets 1-4, respectively. Mean and standard deviation (SD) of thumb-tip force for each group were calculated. To reduce overfitting, 5-fold cross validation was used. Accuracies and losses were analyzed, and a two-sample t-test compared peak accuracies of each ANN and dataset.

Results and Discussion

The mean and distribution of final thumb-tip forces within Dataset 4 revealed the relative contributions of extrinsic muscles (Figure 1). No overlap within 1 SD occurred between groups with a high FPL maximum isometric force and that with a low one. Little overlap occurred between groups of high and low APL maximum isometric force. Both ANNs saw a decrement in performance for datasets which altered more muscles. In the feedforward ANNs, the peak accuracy for Dataset 1 was 93.2%, but 37.4% for Dataset 4. For the LSTM ANNs, the peak accuracy for Dataset 1 was 93.8%, but 34.8% for Dataset 4. Losses became substantially less stable for more complex datasets for both ANNs. Two-sample t-tests revealed that only analysis of Dataset 2 produced significantly different peak accuracies ($p<0.05$), which were higher for the LSTM than the feedforward ANN. Peak accuracies for all datasets were well above random guess.

The decrement in model performance for more complex datasets may be attributable to redundancies in muscle function. Notably, the EPL and EPB are extensors of the thumb, with the APL assisting in extension as well [5]. As Datasets 3 and 4 included changes to combinations of these muscles, the classification task of the ANN became more challenging. Optimization of ANN width and depth may benefit classification [6, 7], as well as the inclusion of more measureable inputs (e.g. kinematics, EMG)

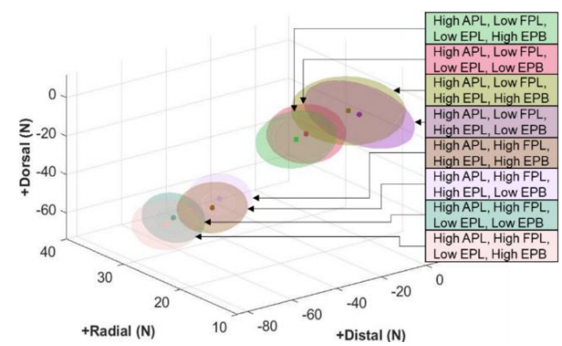

Figure 1: Thumb-tip forces for part of Dataset 4. Ellipsoid centers represent mean force and radii represent 1 SD

Conclusions

Our investigations tested the feasibility of using ANNs to predict muscle parameters from lateral pinch force. This framework is a first step toward estimating subject-specific muscle parameters from minimal, measurable data.

References

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