CREATING PERSONALIZED THUMB MODELS FROM SPARSE SIMULATION DATASETS USING DEEP LEARNING

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Introduction

Despite recent advances in musculoskeletal modelling, current models remain inadequate for personalized medicine. For example, models at the wrist commonly exhibit errors in estimated muscle forces in the range of 20-50%, but these errors can be as high as 180% [1]. While subject-specific models are likely to yield superior performance and thus be better suited for patient care, measuring subject-specific parameters remains time intensive and impractical in a clinical setting. Here, we investigate whether subject-specific parameters can be estimated from easily obtainable clinical measurements (height, weight, pinch force) through the use of deep learning. We specifically examine how increasing force data complexity from 1D to 3D, and from peak forces to time series, improves such estimates.

Methods

We generate unique models by uniformly scaling the height, weight, bone density (BD), tendon slack length (TSL), optimal fiber length (OFL), physiological cross-sectional area (PCSA), and pennation angle (PA) of the bodies of a generic OpenSim lateral pinch model [2]. Scaling factors are selected based on known distributions of each parameter in adults [3,4]. Using 50 random models, we generate activation patterns using computed muscle control (CMC). One of these 50 activation patterns is then randomly chosen for each new model to use in forward dynamics, emulating variability in how people perform a lateral pinch task.

To train neural networks, 50,000 randomly scaled models are generated, and forward dynamics is performed to estimate lateral pinch force. These pinch force estimates, along with height and weight scaling factors, are used as inputs for the neural networks. Eight independent networks are trained, each with a different input representation based on 3 binary choices: (i) forces are either 1D or 3D, (ii) forces are either singular peak force or time series, and (iii) height and weight are either included or excluded.

For each representation of network inputs, an 80/20 train-test split is performed, then 5-fold cross-validation is used on the training data to determine the optimal network hyperparameters: number of hidden layers, learning rate, layer size, and nonlinear activation function. The final neural networks are then trained on the training set using the optimal hyperparameters for each input representation. The root mean square error (RMSE) of the predictions produced on the test set are compared to determine the usefulness of the different input representations for predicting 5 musculoskeletal parameters: BD, TSL, OFL, PCSA, and PA.

Results and Discussion

Our results suggest that height and weight, though most easily obtained, are the least useful for predicting modeling parameters. On average their inclusion as network inputs decreases the RMSE by at most 0.47% for each parameter. Using 3D and time series data (Fig. 1) provides larger improvements, and the combination of all three changes that increase input measurement complexity reduces error more than any one change. Further, changing from 1D peak forces to 3D time series with height and weight reduces error more than changing from distribution-based guesses to estimates based on 1D peak forces.

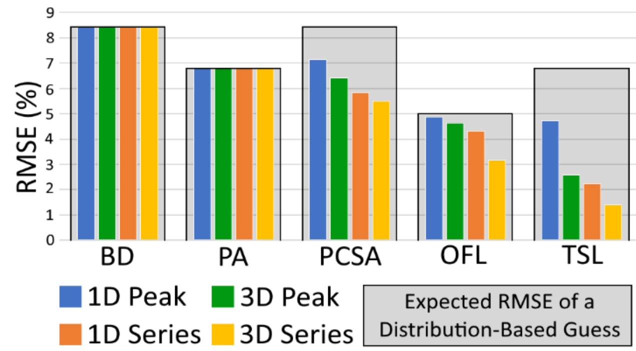

Figure 1: RMSE of parameter estimates generated by neural networks that included height and weight. From left to right, color bars represent increasing complexity of force data representations. Gray boxes are the standard deviation of the parameter distribution, which is equivalent to the expected error of a random guess from that distribution.

We observe that TSL is always the parameter best predicted by the networks. Even with 1D peak forces, TSL scaling can be predicted with less than 5% error, while 3D time series forces can lead to TSL predictions with RMSE less than 1.4%, much less than the 6.67% error expected from random guessing. In contrast, while OFL prediction errors are reduced to 3.1% with 3D time series, other input representations produce errors of 4.3-4.9%, much closer to the expected error random guessing (5%). We find that PA and BD cannot be predicted using lateral pinch forces. We suspect PA is unpredictable because small deviations in near zero angles will not affect force production due to the small angle approximation. Similarly, BD is unpredictable because very small masses and inertias in the hand do not meaningfully affect an isometric pinch task. Use of measurements from additional isokinetic tasks may enable better predictions for BD in future work.

Significance

The results of this study indicate that by using external force sensors and easily obtained biometrics, some musculoskeletal parameters of a human hand models may be quickly personalized to specific simulated subjects. Thus, this work provides the foundation for systems capable of generating personalized models suitable for analysis and guidance during treatment of musculoskeletal pathologies in the hand. Additional tasks, new measurements, and real-world validation with experimental data may enable personalization of more parameters and improve the accuracy of current parameter predictions.

Acknowledgments

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