Transfer Learning with Simulated and Recorded Data Improves Predictions of Upper Extremity Biomechanics

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INTRODUCTION

Machine learning is a powerful tool for modeling complex human movements. However, the high cost of acquiring biomechanical data often limits observations and therefore the generalizability of these models. Meanwhile, there is untapped utility in musculoskeletal models for informing machine learning predictions. Transfer learning, the process of training a machine learning model on one task (e.g. simulated data) and re-purposing this knowledge for another task (e.g. measured data), has therefore emerged as a potential tool for predicting human movement [1,2].

Our objective was to create and validate transfer learning frameworks that use artificial neural networks to model complex upper extremity movements. Specifically, we modeled lateral pinch, a task involving the combined, redundant effort of muscles acting about the wrist and thumb. Our results elucidate the impact of transfer learning on machine learning model accuracy and exemplify how this technique may be used to improve predictive models of human movement.

METHODS

We developed feedforward (FF) and long short-term memory (LSTM) neural networks to regress three-component lateral pinch thumb-tip forces from eight muscle activations. We trained and tested two versions of each neural network. The first was trained solely on recorded data. The second was a transfer-learning model that was pre-trained with simulated data and fine-tuned on recorded data (Fig. 1, left).

To provide observations to the transfer learning models, we generated 6,594 lateral pinch simulations using a thumb model [3] and OpenSim v. 4.1. Each simulation included a unique combination of scaling (young adults [4]) and target force (40 to 80 N). Simulation-derived muscle activations were neural network inputs and thumb-tip forces were outputs.

To train and test the neural networks, we recorded experimental data. These data were recorded from five female and three male, right-handed, young adults (IRB#202202263). Muscle activity was recorded using fine-wire electromyography (EMG) collected at 3000 Hz from eight muscles. Simultaneously, lateral pinch force was collected using a 6-axis force sensor. During data collections, subjects performed three 5-second maximum voluntary contractions of lateral pinch with 30 seconds of rest between each. Each neural network was trained on the same seven subjects' data, with one subject's data used for testing.

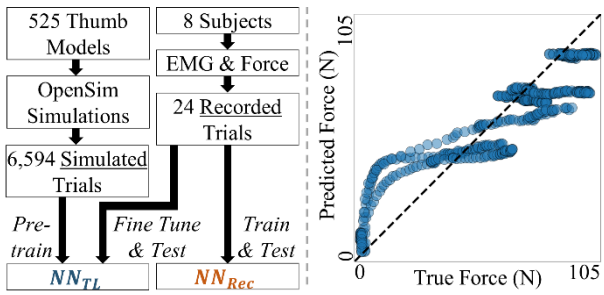

Figure 1: Framework used to develop neural networks informed via recorded data and transfer learning, denoted NN_{Rec} and NN_{TL}, respectively (left). Parity plot for LSTM developed via transfer learning when predicting on the test subject's data (right). The forces displayed represent thumb-tip force magnitude.

RESULTS AND DISCUSSION

Neural networks trained on recorded data alone underperformed relative to their transfer learning counterparts. Test predictions of FF and LSTM models trained only on recorded data had mean absolute errors (MAEs) of 6.9 N and 5.9 N, respectively. By comparison, FF and LSTM models developed via transfer learning achieved MAEs of 6.0 N and 5.6 N. The LSTM developed via transfer learning (Fig. 1, right) outperformed every other model and maintained generalizability to distal and palmar thumb-tip forces. These results indicate that pre-training neural networks on simulation data enhances model generalizability. Furthermore, our approach can be easily adapted and applied to predict other movements.

CONCLUSIONS

Our work suggests that machine learning models of human movement can benefit from the knowledge contained in musculoskeletal simulations. Through continued efforts, models with greater generalizability to real-world conditions may be achieved.

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