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From Simulation to Reality: Predicting Torque with Fatigue Onset via Transfer Learning

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INTRODUCTION

Muscle fatigue, the exercise-induced reduction in a muscle's force-generating capacity [1], is an important factor in the design of myoelectric devices [2] and injury prediction [3]. Multiple works have attempted to capture biomechanical changes with muscle fatigue onset. Despite the relevance and existence of fatigue models, the effects of fatigue are typically ignored in models of human movement [4]. Ignoring the effects of muscle fatigue, especially for sustained or high intensity contractions, can result in considerable uncertainty in predicted outcomes.

Our objective was to improve the prediction of torque in fatiguing upper extremity movements. We selected to predict torque as it is correlated to the decline in muscle force caused by fatigue. Furthermore, predicting changes in torque is valuable for the design of interventions to mitigate the impact of muscle fatigue. Towards this objective, we developed a model of elbow flexion via transfer learning, the process of training a machine learning model on one task (e.g. simulated data) and repurposing this knowledge for another task (e.g. measured data). Through this work, we expected to demonstrate machine learning models trained on simulations and recorded data can predict sustained elbow flexion torque more accurately than those trained on only recorded data.

METHODS

We developed long short-term memory (LSTM) neural networks to regress elbow flexion torque from four muscle activations. We trained and tested two LSTMs. The first was trained solely on recorded data. The second leveraged transfer learning in that it was pre-trained with simulated data and fine-tuned on recorded data (Fig. 1).

For the simulation dataset, we generated 1,701 elbow flexion simulations using an upper extremity model [5] and OpenSim v. 4.1. Each simulation included a unique combination of scaling (young adults [6]) and target torque (30 to 90 Nm, coinciding with previously reported maximum voluntary torques [7,8]). We then processed these data through the muscle fatigue model described by Xia and Frey Law [9]. This model uses compartment theory and control theory to represent a muscle's motor units in active, rested, and fatigued states. We parameterized this model using fatigue and recovery rates for the elbow defined in prior literature [10]. Simulation-derived muscle activations and time were LSTM inputs and dynamic elbow flexion torque was output.

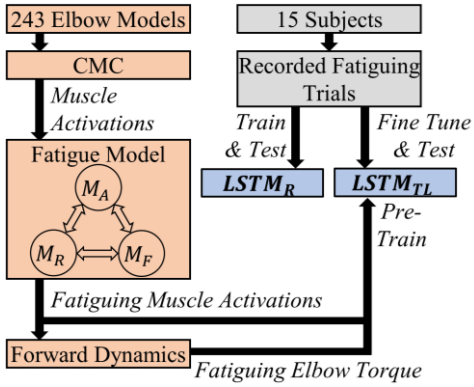

Fig 1: Framework used to obtain data and develop LSTMs (blue) informed via recorded data (gray) and transfer learning, denoted $LSTM_R$ and $LSTM_{TL}$, respectively. Simulated data (orange) were generated via computed muscle control (CMC), a fatigue model, and forward dynamics.

For the experimental dataset, we recorded data from 15 right-handed young adults (6 female, 9 male, 22.3 ± 2.9 years, 1.7 ± 0.05 m, 75.8 ± 14.1 kg) as part of an IRB-approved study (UF IRB #202202263). Muscle activity was recorded using surface electromyography (EMG) of the *biceps*, *brachioradialis*, and *triceps* as well as intramuscular EMG of the *brachialis*. All EMG data were collected at 3000 Hz. Simultaneously, dynamic elbow flexion torque was collected using a Biodex System Pro 4. Participants were positioned at 45º shoulder flexion, 90º elbow flexion, and 90º supination.

During testing, each participant performed three 5-second maximum voluntary contractions (MVCs) of isometric elbow flexion with 10 seconds of rest between. Following the MVCs, each participant performed sustained elbow flexion with a target torque of 80% of their maximum torque. Similar to prior work [8], this fatiguing trial terminated when the participant's torque fell below 70% of their MVC for 3 of 5

seconds. Across both the MVC and fatigue trials, participants received real-time visual feedback of their torque and verbal encouragement.

We compared the prediction accuracies of the LSTM trained solely on recorded data with those of the model developed via transfer learning. Each LSTM was trained on the same twelve subjects' data, with three subjects' data used for testing. Specifically, we compared the root mean square error (RMSE) and mean absolute error (MAE) of each LSTMs' predictions on the test subjects' data.

RESULTS AND DISCUSSION

The LSTM trained on recorded data alone underperformed relative to its transfer learning counterpart. The LSTM trained only on recorded data predicted test subject torques with an RMSE and MAE of 18.3 Nm and 15.5 Nm, respectively. By comparison, the LSTM developed via transfer learning achieved an RMSE and MAE of 16.0 Nm and 13.2 Nm, respectively (Fig. 2). These results indicate that pre-training machine learning models on simulated, fatiguing elbow flexion torques improves predictions on real-world data.

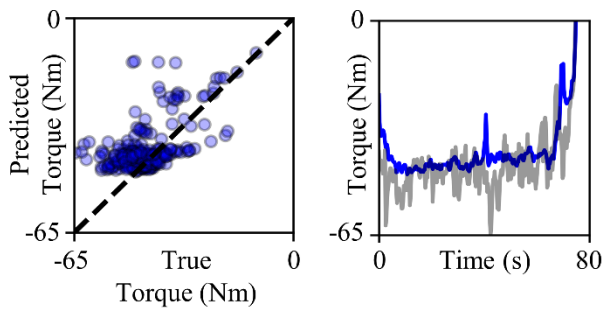

Fig 2: Parity plot (left) and raw torque prediction (right) from $LSTM_{TL}$ on one test subject's data. Gray data on right represent recorded torque data, while blue represents $LSTM_{TL}$ predictions.

Both models predicted changes in elbow flexion torque with fatigue onset (i.e., the shape of the curve) relatively well. However, predicting the magnitude of the torque was considerably more challenging. For example, the LSTM developed via transfer learning predicted one test subject's elbow flexion torque with an MAE exceeding 23 Nm. Yet, shifting the predicted torque of the entire fatigue trial by a constant offset yielded an MAE of 3.3 Nm (Fig. 3). This substantial decrease in MAE suggests the LSTMs would improve with the inclusion of features that indicate the magnitude of the torque, such as the initial torque for each trial and the subject's maximum voluntary torque. Furthermore, features such as sex, physical function, metabolic parameters, and anthropometric data may further improve the LSTM's predictions.

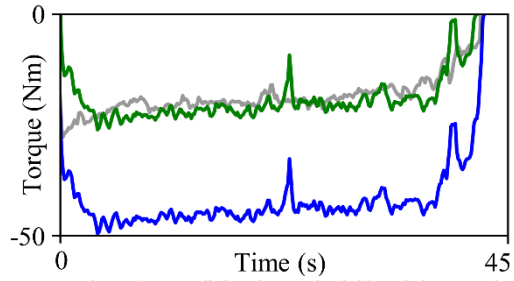

Fig 3. Sample of raw (blue) and shifted (green) torque predictions from $LSTM_{TL}$ on the test subject associated with the poorest raw prediction accuracy. Recorded torque data is shown in gray. The depicted shift was calculated as the difference between means of the raw predicted and recorded torques.

Pre-training the LSTM on simulated data improved torque predictions, exemplifying the potential of simulations for informing machine learning models. The computational efficiency of simulated biomechanical data, and the availability of open-source repositories means there are abundant, available simulations that can be used for predicting real-world biomechanics. Future works may apply our transfer learning strategy to model populations and tasks beyond elbow flexion in young adults.

CONCLUSIONS

Our results exemplify how our transfer learning framework can be used to expand the utility of simulated datasets and yield models robust to the onset of muscle fatigue. Alone, simulations can be encumbered by assumptions. Yet, accompanying these data with measurements can yield models generalizable to a wide variety of real-world biomechanical systems.

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