TRANSFER LEARNING FOR BIOLOGICAL JOINT MOMENT ESTIMATION IN STROKE POPULATIONS

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Introduction: Biological joint moment estimation plays a crucial role in determining control parameters for assistive exoskeletons, which have the potential to enhance mobility in stroke populations. An increasing availability of human biomechanics datasets has enabled the estimation in able-bodied populations using state-of-the-art deep learning models [1,2]. However, there is a lack of well-represented datasets in clinical populations such as stroke due to the heterogenous nature of stroke gait as well as the time, cost, and resource intensive nature of biomechanical data collection. Thus, machine learning based joint moment estimation in stroke populations has not been explored. Transfer learning is a machine learning technique that leverages knowledge from a source task to improve the performance on a target task, especially when the target task lacks high-quality data [3]. In this study, we employed transfer learning to estimate hip joint moments for a stroke subject by fine-tuning a Temporal Convolutional Network (TCN) model trained on an able-bodied biomechanics dataset. We hypothesized that retraining the able-bodied model using minimal stroke data would improve model performance on the stroke dataset.

Methods: We used a 5-subject able-bodied (AB) dataset consisting of 21 cyclic and acyclic tasks, with similar task representation as [4] for training. Unilateral data were collected using IMUs placed on the back, pelvis, thigh, shank and foot, as well as pressure insoles corresponding to the paretic side of the stroke (ST) subject. Three-axis accelerometer and gyroscope data from 5 IMUs, along with the vertical ground reaction force at the foot were used as input features and hip joint moment was used as the label for training a model. A TCN model [5] was implemented in accordance with previous literature [1,6] where it was validated for joint moment estimation in able-bodied populations. We used root mean square error (RMSE) as our loss function. The model was trained using leave-one-out cross fold validation, where subjects were 'left-out' for testing and validation each and the rest were used for training. We used a single subject stroke dataset consisting of 4 walking tasks of which 2 were used for testing and retraining. The linear output layer of the best-performing AB model was retrained using ST data (4-5 gait cycles from 1 task, 5 seconds), while the rest of the layers were frozen. Testing was performed in three parts: AB data was tested on the AB model (AB/AB), ST data was tested on the AB model (ST/AB), and ST data was tested on the retrained ST+AB model (ST/ST+AB) using RMSE as the comparison metric.

Results & Discussion: As shown in Fig. 1 (a), RMSE increased on testing ST data on the AB model due to differences in stroke gait patterns as compared to able-bodied patterns (0.149 Nm to 0.465 Nm). Supporting our hypothesis, post retraining with a small subset of ST data, the model learned subject-specific stroke gait patterns, reducing RMSE from 0.465 Nm to 0.336 Nm (~27% decrease). Visual comparison of the time-varying plots (b)-(d) in Fig.1 also validates the hypothesis.

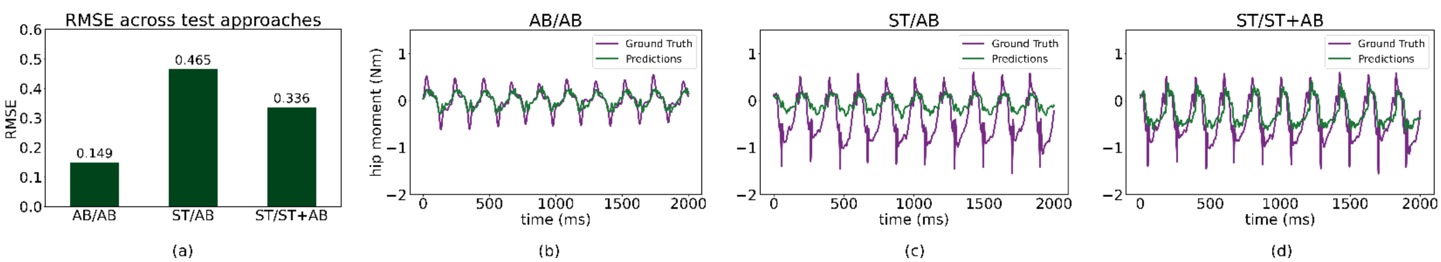

Figure 1: (a) RMSE across three test approaches. (b)-(d) Model predictions vs ground truth hip moments across time (ms) for three test approaches

Significance: Our study applied transfer learning to enable joint moment estimation in stroke populations where data availability poses a challenge to standard ML approaches. Our approach also allowed for customization of a general model to a patient with minimal data (0.14% of the size of able-bodied training data) causing a 27% decrease in error, eliminating computational costs associated with training custom models. This technique shows promise in facilitating tailored approaches to patient-specific exoskeleton control to aid mobility and rehabilitation. While this pilot study encourages the use of transfer learning for improving model performance on stroke data, further work is necessary to quantify the amount of retraining data, select optimal retraining tasks, and develop robust transfer learning pipelines to ensure satisfactory outcomes in joint moment estimation.

References:

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