GENERALIZABLE DEEP LEARNING MODEL ENABLES PREDICTION OF FUTURE PHYSIOLOGICAL STATES DURING PERTURBED LOCOMOTION

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Introduction: Falling is the leading cause of injury related death in older adults [1]. Exoskeletons have the potential to augment balance to reduce fall rate, however, classical control strategies are hand engineered and often rely on the cyclic nature of locomotion and are therefore not well suited for transient movements. Recently, a deep learning-based task-agnostic controller based on the user's physiological state was shown to decrease metabolic cost across cyclic and non-cyclic tasks, showing this controller's ability to generalize [2]. However, the effectiveness of this approach for perturbation recovery has not been investigated. We anticipate that the timing of joint moment-driven exoskeleton assistance will differ for approaches that aim to augment balance. Metabolic cost-reducing approaches apply joint moment assistance that is delayed relative to the user's joint moment, while faster-than-human assistance has proven beneficial for balance augmentation [3][4]. The aim of this study is to (1) optimize a deep learning model that predicts future joint moments, enabling faster-than-human control and (2) investigate the ability of this model to generalize to perturbation conditions outside of the training set, to test the robustness of our approach in handing novel perturbations. We hypothesized that (1) estimation accuracy will decrease as forecasting increases and (2) estimation accuracy will be lower for held-out-conditions.

Methods: We collected a training data set of able-bodied individuals (N=17) undergoing translational ground perturbations. The perturbation trials systematically varied perturbation magnitude, onset timing, and direction (Fig. 1A). We collected motion capture, force plates, and inertial measurement unit (IMU) data. We calculated inverse dynamics to obtain frontal and sagittal plane hip moments. The full experimental protocol has been previously described by Leestma et al. [3]. We trained a series of temporal convolutional networks (TCN) that used wearable IMUs (pelvis, torso, and bilateral dorsal foot, shank, thighs) to predict joint moments. First, we trained models that forecasted joint moments 0ms (estimation at current time), 40ms, 80ms, and 120ms into the future. We also conducted a leave-n-conditions-out validation where we held out pairs of directions to test the ability of the models to generalize to unseen perturbation conditions. We computed the estimation accuracy using R^2 and root mean square error (RMSE).

Results & Discussion: As hypothesised, model accuracy decreased as forecasting increased. This is expected as sensor input data is further away from the outcomes we are estimating. Still, most average R^2 values for estimating hip moment across forecasting times were above 0.80 except for frontal plane at our furthest forecasting (Fig. 1B). This accuracy has been previously shown to allow for highly controllable exoskeletons [2]. Contrary our second hypothesis, we found that estimation accuracy was similar when conditions were held out compared to when the full training set was used (Fig. 1C). This might be due to the similarity between the held-out conditions and the ones still included in training. This effectively shows our model's ability to generalize to unseen perturbation directions.

Future work will (1) deploy our forecasting estimators to control a 2-degree-of-freedom hip exoskeleton and (2) further explore the generalizability of our model by excluding different groups based on perturbation magnitude and timing.

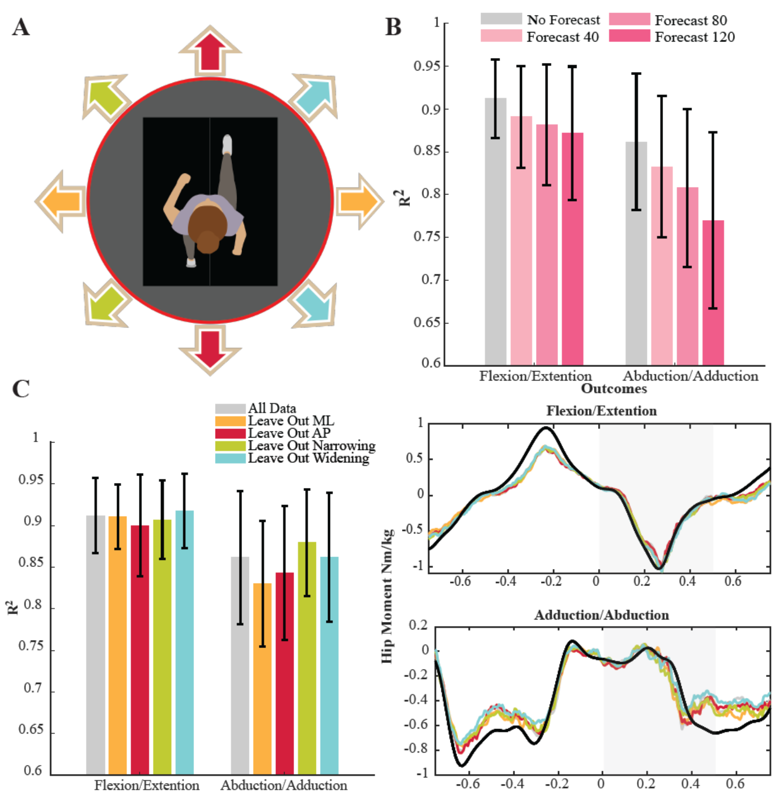

Figure 1: (A) Platform translations were delivered in the mediolateral and anterior posterior directions as well as the respective diagonals. (B) Joint moment estimation R^2 across forecasting times. (C) Joint moment estimation R^2 for direction pairs excluded for the training set. Time series plots show ground truth (black) and estimated (colors) joint moment for a representative trial for the excluded direction pairs. The perturbation happens at time 0 and the shaded area represents the proposed exoskeleton actuation window.

Significance: We demonstrate (1) deep learning models can reliably estimate future physiological states which enables faster-than-human exoskeleton assistance and (2) our model can generalize to unseen perturbations. Together, this type of controller shows potential to assist perturbed locomotion in highly dynamic real-world environments.

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References: [1] Kakara et al. (2023), *MMWR Morb Mortal Wkly Rep;* [2] Molinaro & Scherpereel et al. (2024), *Nature;*[3] Franks et al. (2021), *Wearable Technologies;* [4] Beck et al. (2023), *Science Robotics;* [5] Leestma et al. (2023), *J. Exp Biol.*