Discrepancy modeling of ankle exoskeleton walking

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I. Introduction

Ankle exoskeletons (exos) are used to assist walking or improve gait following neurological injuries [1]. Changes in gait in response to exos are highly heterogeneous [1]. Identifying interpretable dynamics governing exo responses may highlight individualized mechanisms driving these responses. Yet, if standard measurements (kinematics and muscle activity) can encode the dynamics of exo responses is unclear.

Discrepancies are mismatches between system and model dynamics. Discrepancy models disambiguate missing dynamics from noise and may quantify exo responses. For example, our ability to model myoelectric responses (*i.e.*, discrepancies) to ankle exo stiffness from data is limited [4]. We investigated if discrepancies between zero- and high-stiffness exo walking could be identified using kinematic and myoelectric data. We hypothesized that zero-stiffness dynamics augmented by a discrepancy model of exo response would predict kinematic and myoelectric second derivatives of high-stiffness walking with greater accuracy than zero-stiffness dynamics alone.

II. Methods

We used published kinematic and myoelectric data [2] from 11 unimpaired adults during four-minute treadmill walking trials with bilateral passive ankle exos under zero-stiffness and high-stiffness conditions. To explain the maximum discrepancy variance given the data, we modeled discrepancies due to exo stiffness using a feedforward neural network (NN) [3]. We used gait phase, 10 lower-limb joint angles (OpenSim 3.3), 14 muscle activity states (Delsys Inc), and their derivatives as model inputs to predict the second derivatives of right leg joint angles and muscle activity (Fig. 1).

We fit NN models for 1) baseline dynamics, M_0, using the zero-stiffness data, 2) discrepancy dynamics, M_D, using the error between the high-stiffness outputs and the M_0 model predictions using high-stiffness data, and 3) reference dynamics, M_H, using the high-stiffness data. We compared the ability of augmented dynamics, M_{0+D}, and high-stiffness dynamics to predict the high-stiffness derivatives. We identified differences in model prediction accuracy using coefficient of determination (R^2) and Wilcoxon Signed-Rank tests with a Holm-Sidak Stepdown correction ($\alpha = 0.05$).

III. Results and Discussion

All M_{0+D} predictions were more accurate than M_0 predictions ($p < 0.042$), explaining 92-96% of median kinematic variance and 66-78% of myoelectric variance explained by M_H predictions (Fig. 1). These results indicate that discrepancy models encoded most of the missing dynamics. The 1-9% of variance not accounted for by M_D is likely due to noise limiting disambiguation of missing dynamics. However, M_H accounted for only 72-82% of the variance in muscle activity, 12% less than one study using musculoskeletal simulation to predict muscle activity of normal walking [4]. Other measurements, such as musculotendon dynamics, may be needed to explain additional variance in myoelectric discrepancies.

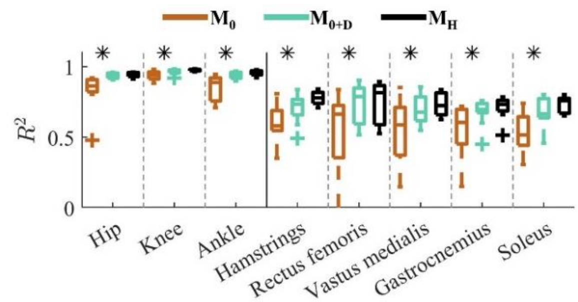

Fig. 1 – Prediction accuracies of the second derivatives of joint angles and muscle excitations of the high-stiffness condition. Asterisks denote significant differences in accuracy between the baseline (M_0) and augmented (M_{0+D}) models. The M_H model reflects the maximum expected prediction accuracy.

IV. Conclusion

We showed that discrepancy models can encode changes in dynamics with ankle exos using kinematic and myoelectric measurements up to the limits imposed by measurements and noise. However, additional measurements are needed to encode the dynamics of muscle activity with exos. Reducing model complexity and identifying additional measurements explaining responses are important areas of future research.

Acknowledgments

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