Robotic Human Enhancement Enabled through Wearable Hip Exoskeletons Capable of Community Ambulation

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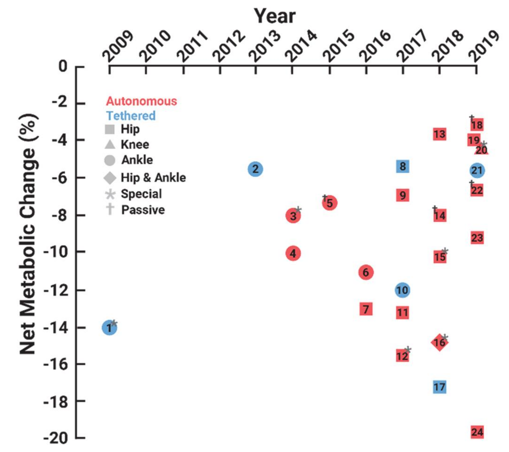
Introduction

- Human hip augmentation has been shown to have high impacts in improving gait [6].
- Exoskeleton technology can be optimized to maximize performance from both a hardware [4, 23] and controller perspective [1, 13, 16].
- Incorporating myoelectric sensing into the exoskeleton controller also provides the opportunity to predict the wearer's future intent [3, 17].
- Estimation of the user and environmental state can be used to provide seamless assistance across ambulation modes [5, 11, 12].



Exoskeleton studies vs. metabolic cost benefit [6]

Advanced Hip Exoskeleton Designs for Specialized Use Cases

High Torque, Robust Interface

Specifications

Peak Torque: ~ 120 Nm

Max Continuous Torque: ~ 50 Nm

Max Speed: ~ 8 rad/sec

Transmission: 50:1

Total Mass: 6 kg

SEA-driven Bilateral Robotic Hip Exoskeleton [23]

Lightweight, Highly Transparent

Specifications

Peak Torque: ~ 15 Nm

Max Continuous Torque: ~ 9 Nm

Max Speed: ~ 33.3 rad/sec

Transmission: 9:1

Total Mass: 4.5 kg

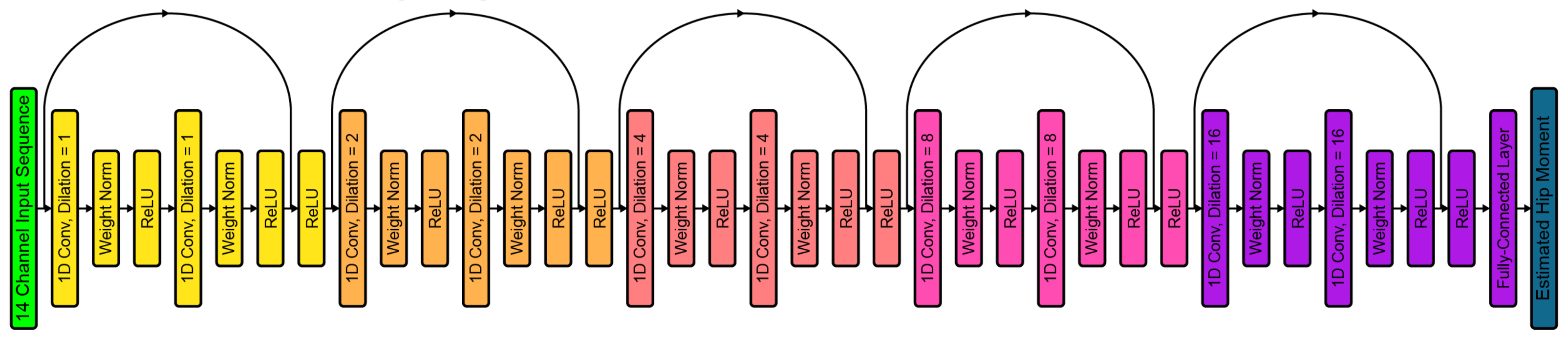
Direct-driven Bilateral Robotic Hip Exoskeleton

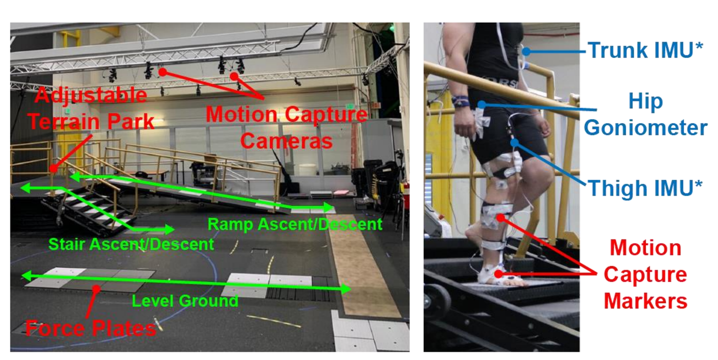
Hip Moment Estimation for Exoskeleton Control

- Estimating the user's biological joint moment using wearable sensors could provide a single, continuous gait variable to dynamically modulate assistance [9].
- Neural networks can predict biological joint moments using wearable sensor data [17] and can generalize to unseen environments [19].
- Implementing the neural network in the exoskeleton control loop reduces the user's metabolic cost of walking with the potential of task-invariant control.

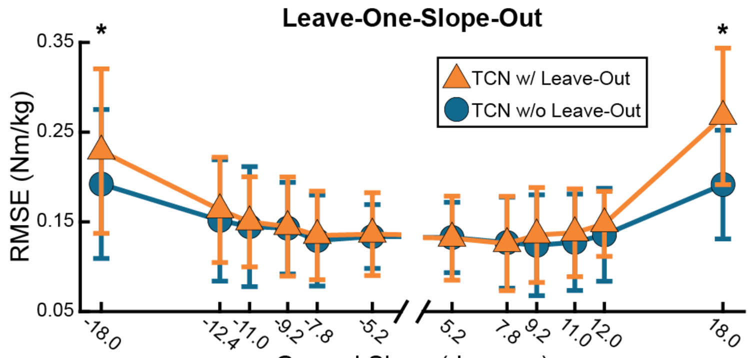
Offline Hip Moment Estimation and Prediction

- Hip goniometer and IMU data from our opensource dataset enabled a temporal convolutional network to estimate hip torques with an R^2 of 0.88 [19].



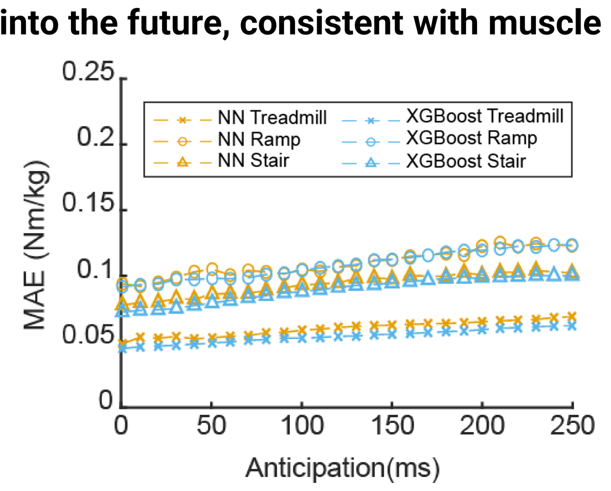


Experimental Setup for Collecting Wearable Sensor Data during Overground Ambulation

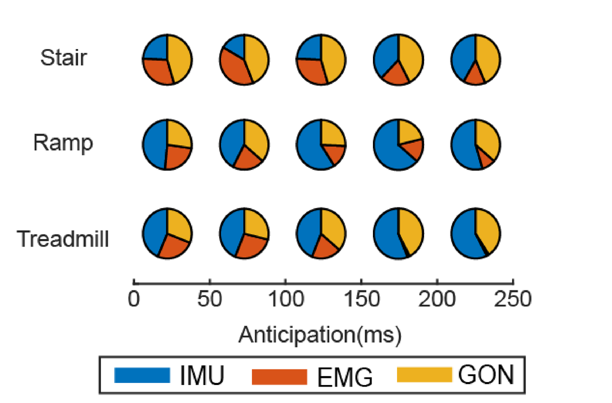


Model Generalization to Hold-Out Ambulation Conditions (i.e., ground slopes and stair heights)

- Adding EMG data as a model input improves joint moment prediction when anticipating up to 150 ms into the future, consistent with muscle electromechanical delay [17].



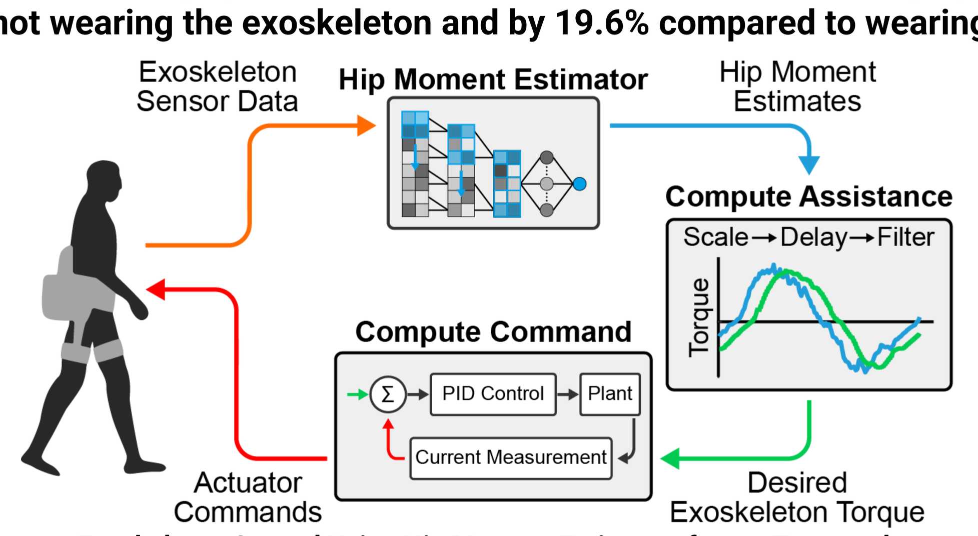
Model Prediction Performance based on Ambulation Mode and Anticipation Time



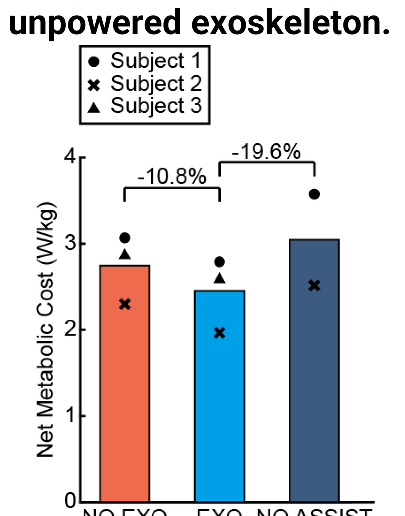
Sensor Type Selection based on Ambulation Mode and Anticipation Time

Hip Exoskeleton Control Using Neural Network-Based Hip Moment Estimates

- Using hip exoskeleton encoder and IMU data as input, we implemented a user-independent temporal convolutional network for estimating the user's sagittal hip moments in real-time.
- The resulting system reduced the metabolic cost of walking by an average of 10.8% compared to not wearing the exoskeleton and by 19.6% compared to wearing the unpowered exoskeleton.



Exoskeleton Control Using Hip Moment Estimates from a Temporal Convolutional Network



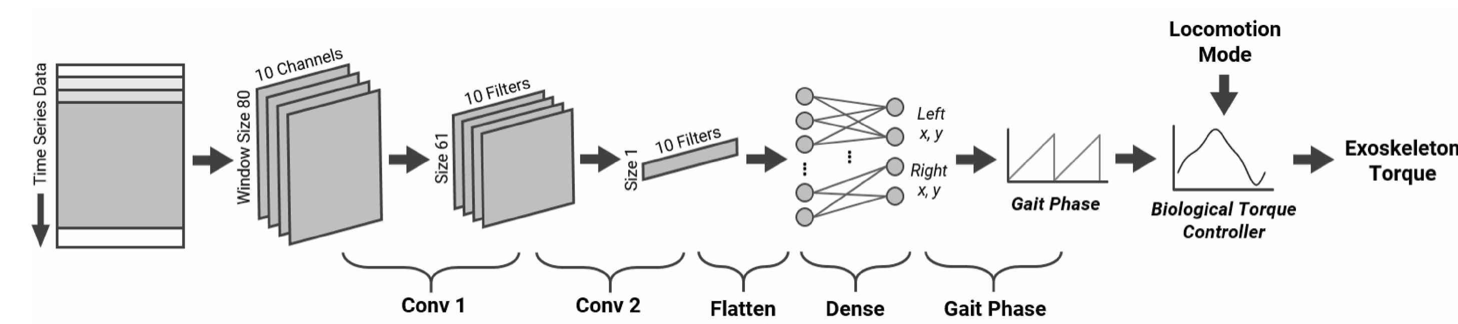
User Metabolic Cost With and Without Using the Novel Controller

User-Independent & Adaptive State Estimation

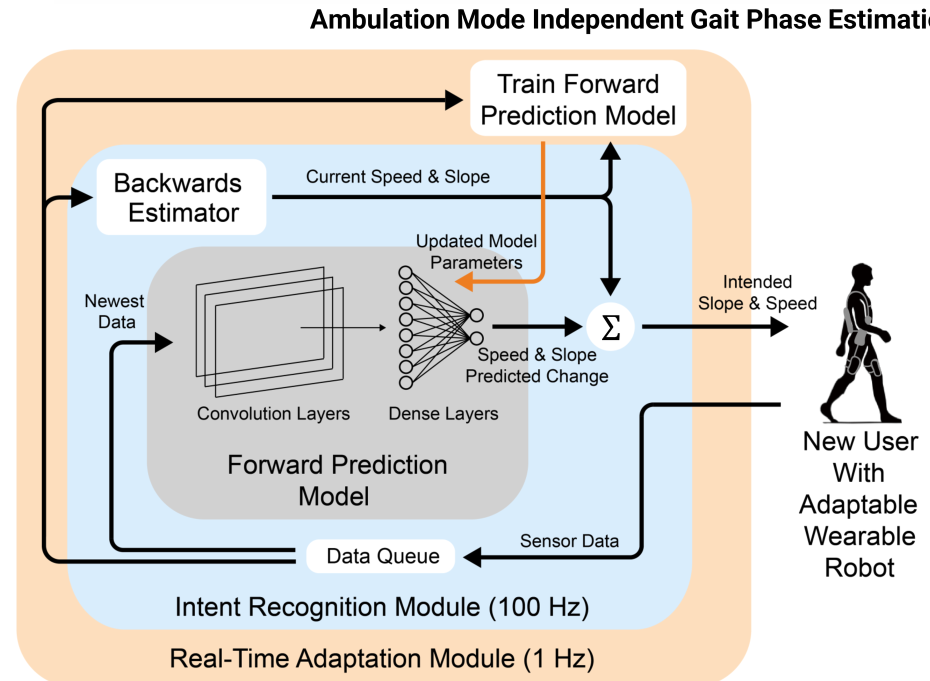
- Estimation of the user and environmental states enable exoskeleton control strategies to change with changes in the user's needs [5, 11, 12].
- Autonomously updating the state estimators online, exoskeleton controllers can adapt with changes in environment and user.

Self-Adaptive Gait Phase Estimation

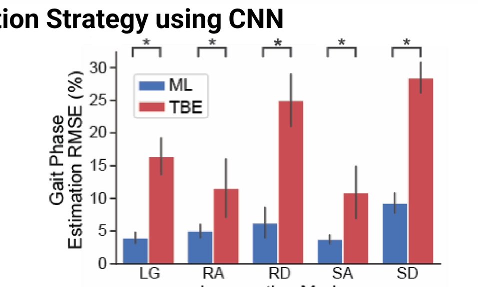
- Using a convolutional neural network, exoskeleton sensor data can be used to estimate gait phase independent of user and ambulation mode [12].
- By autonomously labeling the incoming exoskeleton sensor data and updating the neural network, the gait phase estimator can increase in accuracy by 67%.



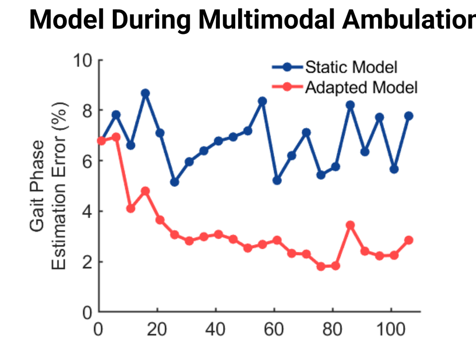
Ambulation Mode Independent Gait Phase Estimation Strategy using CNN



Online Adaptation Framework for Autonomously Adapting the Gait Phase Estimator Online



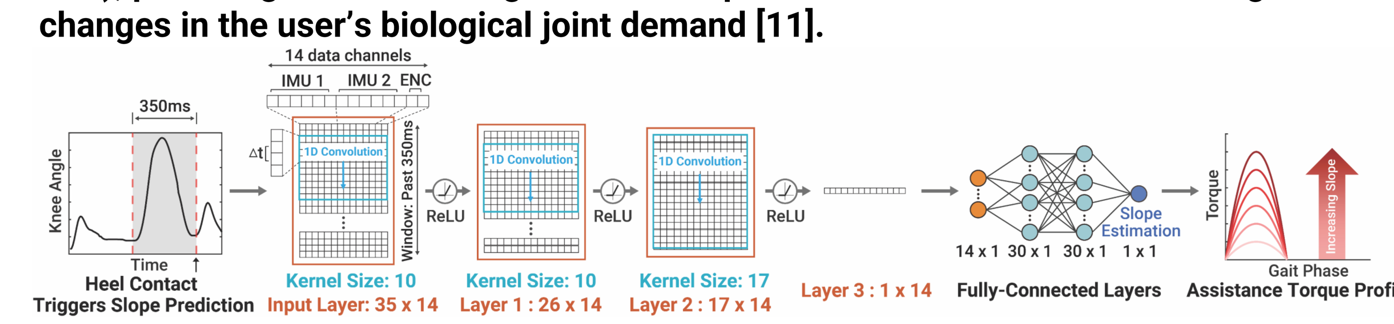
Online RMSE of the Static Gait Phase Model During Multimodal Ambulation



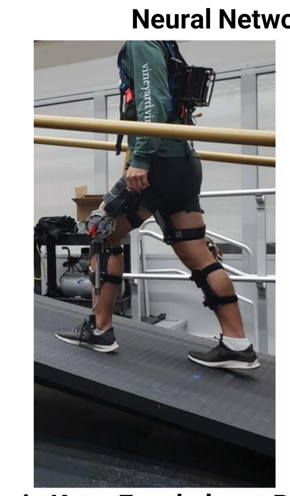
Online RMSE of the Static and Adaptive Gait Phase Model During Level Walking

Predicting Changes in the Environment

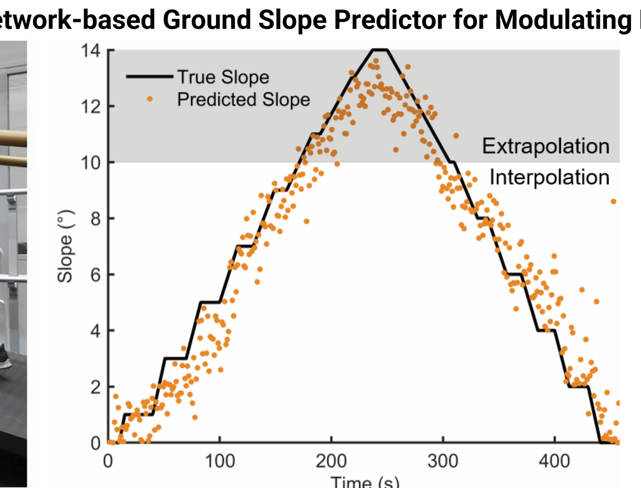
- A deep learning framework enabled accurate predictions of the ground slope (RMSE of 1.5°), providing a reference signal used to update exoskeleton assistance magnitude with changes in the user's biological joint demand [11].

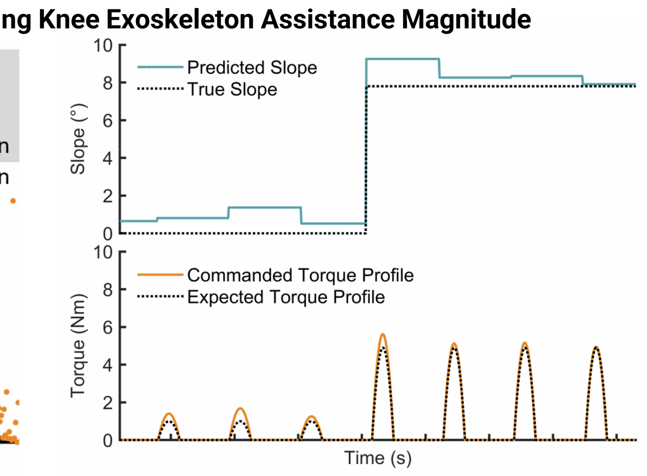


Neural Network-based Ground Slope Predictor for Modulating Knee Exoskeleton Assistance Magnitude



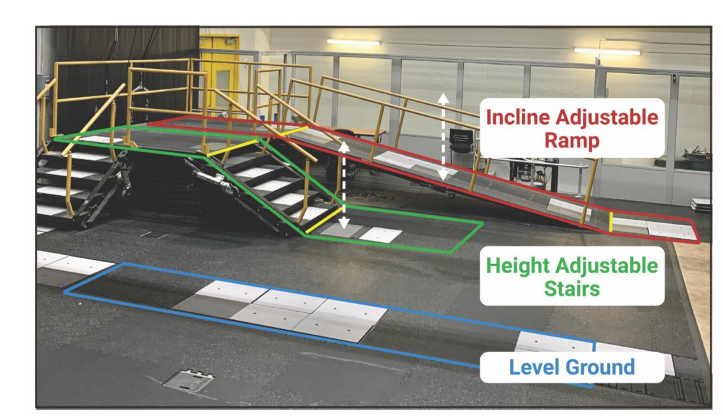
Robotic Knee Exoskeleton Running Real-Time Slope Predictor

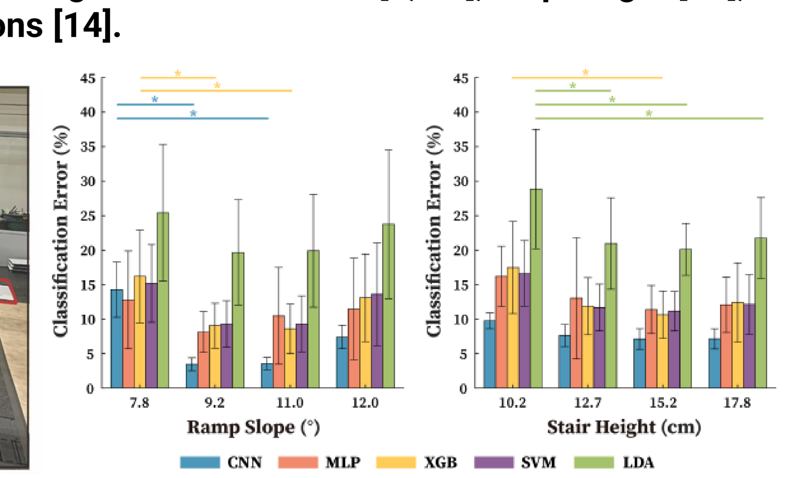




Real-Time Slope Prediction and the Resulting Changes in Exoskeleton Assistance

- Based on offline analyses, deep learning methods can be extended to estimate and predict many user and environmental states, including ambulation mode [8, 21], step length [15], walking speed [3], and stop/start transitions [14].





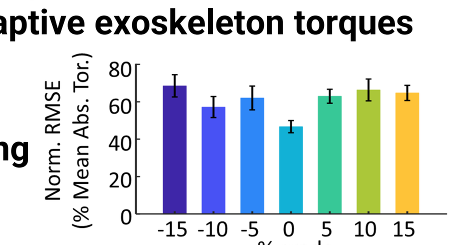
Offline Analysis of Continuous, User-Independent Ambulation Mode Classification

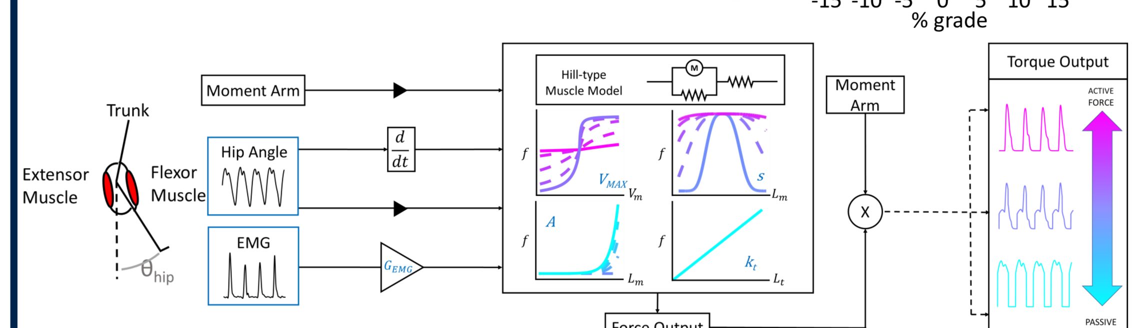
Electromyography for Enhanced Exoskeleton Studies

- Hybrid neuromuscular models use measured muscle activity and kinematics to emulate the underlying human joints [10].
- Measured muscle activity using electromyography (EMG) can be used as a proxy for rapidly estimating the user's metabolic cost.

Hybrid Neuromuscular Model (NMM) Based Controller

- Using EMG and hip joint angle as inputs, a NMM model can mimic the hip joint, producing adaptive exoskeleton torques across locomotion modes [10].
- Optimizing the model for level walking generalized well to walking on inclines and declines [22].

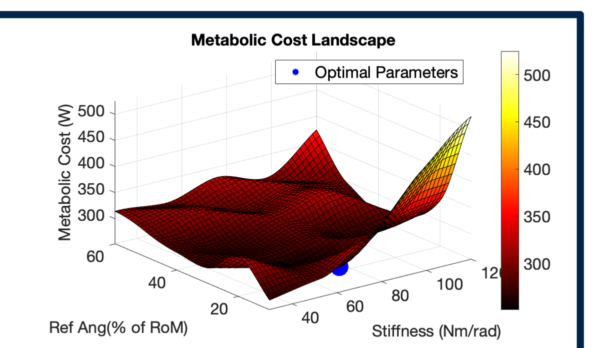


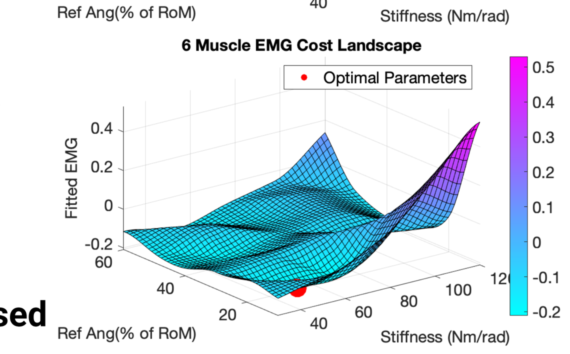


Framework and Results for Hybrid Neuromuscular Model-Based Exoskeleton Control

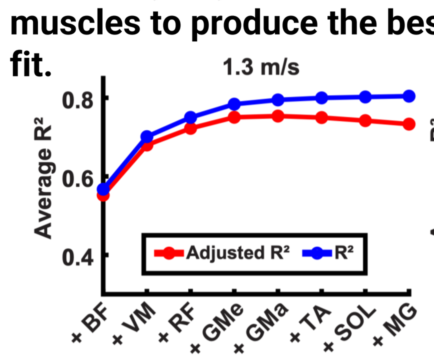
EMG for Control Optimization

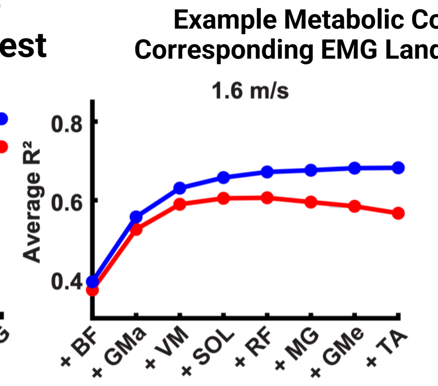
- Multi-channel EMG can be used to rapidly and non-invasively estimate the human's metabolic cost.
- Multivariable linear regression analysis was used to identify key lower-limb muscles to produce the best fit.





Example Metabolic Cost & Corresponding EMG Landscapes





Resulting R^2 as more Muscles are Included in Metabolic Estimation Model

Resulting Publications

[1] . Kang *et al.*, "The effect of hip assistance levels on human energetic cost using robotic hip exoskeletons," RA-L, 2019.
[2] A. Groff *et al.*, "Control Strategies of a Powered Assist Hip Exoskeleton in Subjects with Stroke," AAOP, 2019.
[3] I. Kang *et al.*, "Electromyography (EMG) Signal Contributions in Speed and Slope Estimation Using Robotic Exoskeletons," ICORR, 2019.
[4] S. E. Lee *et al.*, "Investigating the impact of the user interface for a powered hip orthosis on metabolic cost and user comfort: a preliminary study," Prosthet Orthot Int, 2021.
[5] I. Kang *et al.*, "Real-Time Neural Network-Based Gait Phase Estimation using a Robotic Hip Exoskeleton," TMRB, 2020.
[6] G. S. Sawicki *et al.*, "The exoskeleton expansion: improving walking and running economy," J Neuroeng Rehabil, 2020.
[7] D. Lee *et al.*, "Effects of Assistance during Early Stance Phase Using a Robotic Knee Orthosis on Energetics, Muscle Activity and Joint Mechanics during Incline and Decline Walking," TNSRE, 2020.
[8] I. Kang *et al.*, "Continuous locomotion mode classification using a robotic hip exoskeleton," BioRob, 2020.
[9] D. Molinaro *et al.*, "Biological Hip Torque Estimation using a Robotic Hip Exoskeleton," BioRob, 2020.
[10] B. Shafer *et al.*, "Neuromechanics and energetics of walking with an ankle exoskeleton using neuromuscular-model based control: a parameter study," Front. Bioeng. Biotechnol, 2021.
[11] D. Lee *et al.*, "Real-Time User-Independent Slope Prediction Using Deep Learning for Modulation of Robotic Knee Exoskeleton Assistance," RA-L, 2021.
[12] I. Kang *et al.*, "Real-Time Gait Phase Estimation for Robotic Hip Exoskeleton Control During Multimodal Locomotion," RA-L 2021.
[13] D. Lee *et al.*, "Biomechanical Comparison of Assistance Strategies Using a Bilateral Robotic Knee Exoskeleton," TBME, 2021.
[14] H. M. Cho *et al.*, "Real-Time Walk Detection for Robotic Hip Exoskeleton Applications," ISMR, 2022.
[15] H. Jin *et al.*, "Wearable Sensor-Based Step Length Estimation During Overground Locomotion Using a Deep Convolutional Neural Network," EMBC, 2021.
[16] G. Choi *et al.*, "Effect of Assistance Timing in Knee Extensor Muscle Activation during Sit-to-Stand Using a Bilateral Robotic Knee Exoskeleton," EMBC, 2021.
[17] J. Camargo *et al.*, "Predicting biological joint moment during multiple ambulation tasks," J. Biomech., 2021.
[18] M. Shepherd *et al.*, "Deep Learning Enables Exoboot Control to Augment Variable-Speed Walking," RA-L, 2022.
[19] D. Molinaro *et al.*, "Subject-Independent , Biological Hip Moment Estimation during Multimodal Overground Ambulation using Deep Learning," TMRB, 2022.
[20] J. Li *et al.*, "Design and Validation of a Cable-Driven Asymmetric Back Exosuit," T-RO, 2021.
[21] I. Kang *et al.*, "Subject-Independent Continuous Locomotion Mode Classification for Robotic Hip Exoskeleton Applications," TBME, submitted July 2021.
[22] B. Shafer *et al.*, "Emulator-based Optimization of Semi-active Hip Exoskeleton Impedance Control Across Walking Speeds," TBME, submitted November 2021.
[23] I. Kang *et al.*, "Optimizing Series Elastic Actuator Design for Hip Exoskeleton-Assisted Dynamic Locomotion," J. Mech. Robot., submitted January 2022.