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

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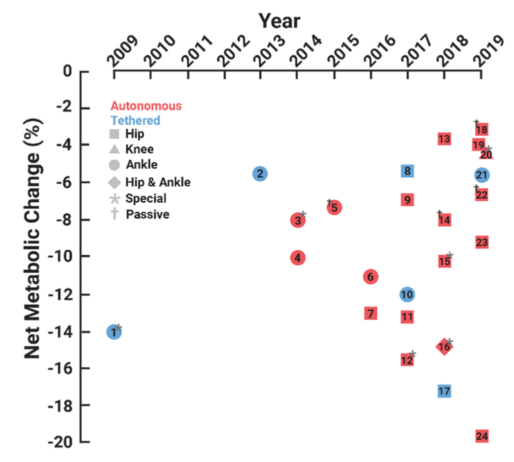
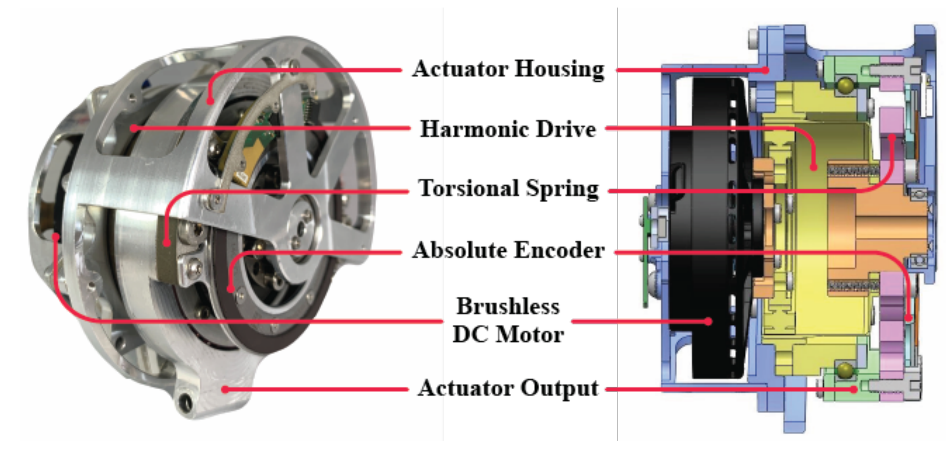
Introduction

- Human hip augmentation has been shown to have high impacts in improving gait.
- Exoskeleton assistance has been optimized to maximize performance from both hardware and controller perspective (Lee, JPO 2020)
- Incorporating myoelectric sensing into the exoskeleton controller also provides the opportunity to predict the wearer's future intent.
- Estimation of the user and environmental state can be used to provide seamless assistance across ambulation modes.



Exoskeleton studies vs. metabolic cost benefit (Sawicki, JNER 2020)

Advanced Hip Exoskeleton Design



Harmonic Drive-based Series Elastic Actuator

SEA-driven Bilateral Robotic Hip Exoskeleton

Exoskeleton Specifications

Peak Torque: ~ 120 Nm

Max Continuous Torque: ~ 50 Nm

Max Speed: ~ 8 rad/sec

Torque Bandwidth: 13 Hz

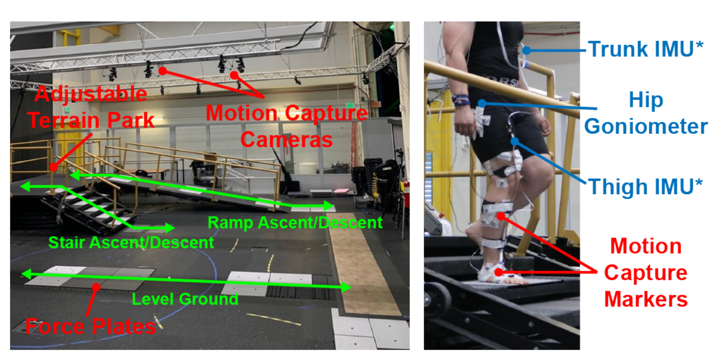
Actuator Weight (x2): 2.194 kg

Biological Joint Moment Estimation

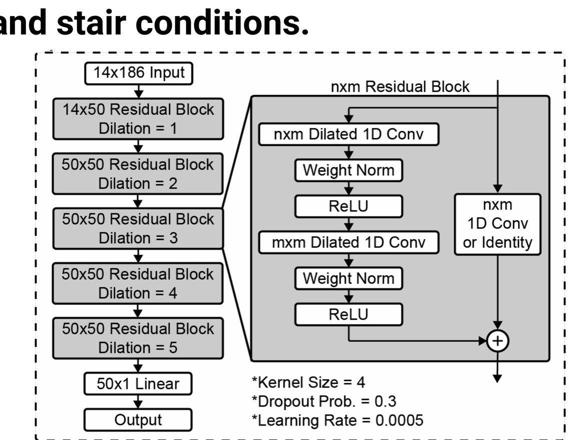
- Estimating user's biological joint moment using wearable sensors could provide a single, continuous gait variable to dynamically modulate assistance (Molinaro, BioRob 2020).
- Deep neural networks can estimate biological hip moment of a novel user from wearable sensor data and generalizes to unseen gait contexts (Molinaro 2021 – In Prep).
- Machine learning models can anticipate future joint moments, which are improved by EMG data when anticipating up to 150 ms into the future (Camargo, TBME 2021 – Under Review).

User-Independent Hip Moment Estimation

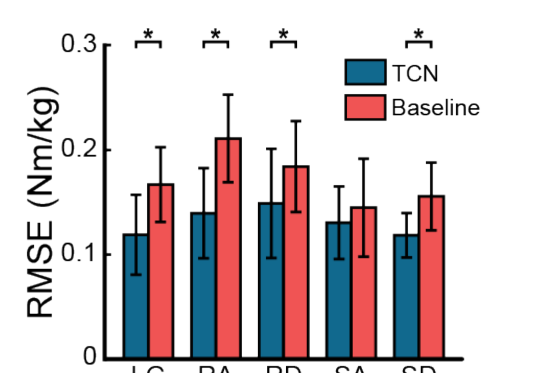
- A temporal convolutional network was used to estimate flexion/extension hip torque using hip goniometer and IMU data, trained using torque from inverse dynamics (0.13 Nm/kg overall RMSE).
- The model outperformed a baseline method ($p < 0.05$) common to exoskeleton control and generalized well to unseen mode transitions and ramp and stair conditions.



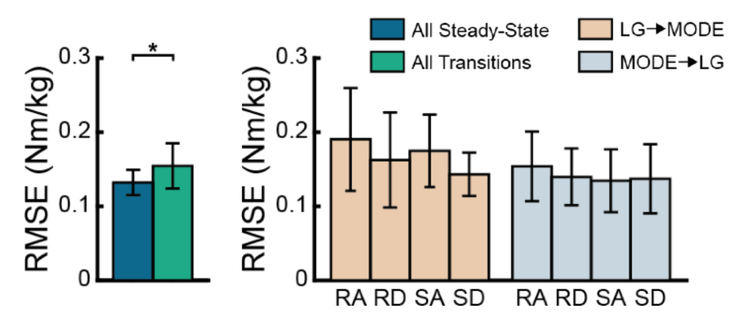
Experimental Setup for Collecting Wearable Sensor Data during Overground Ambulation



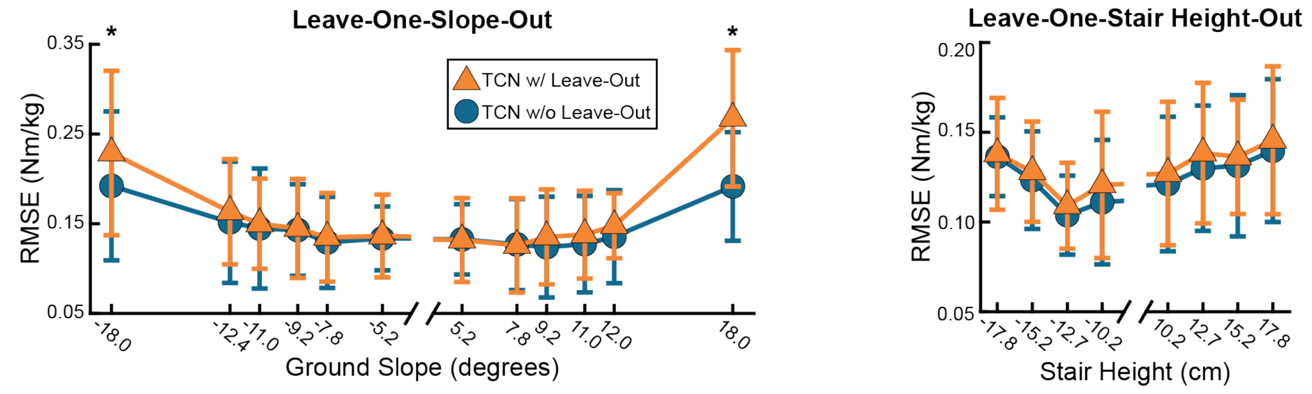
Best Model (Temporal Convolutional Network)



Overall Joint Moment Estimation Performance Compared to Baseline Method



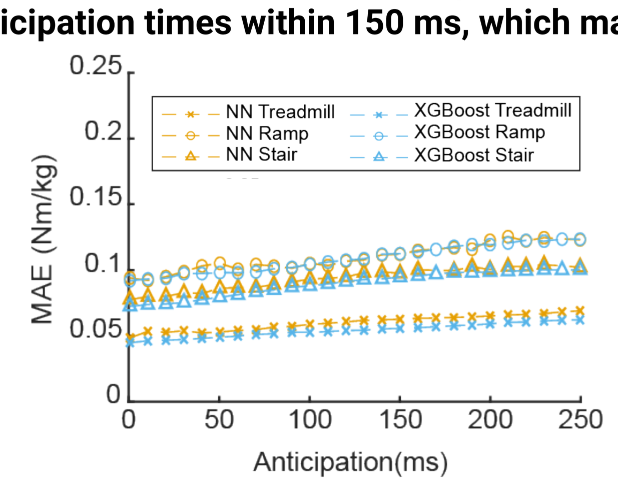
Model Generalization to Ambulation Mode Transitions



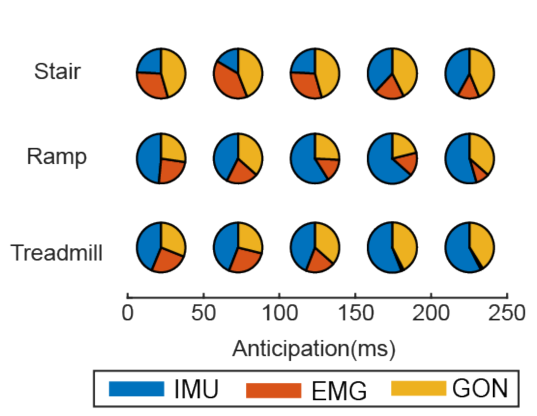
Model Generalization to Hold-Out Ambulation Conditions (i.e., ground slopes and stair heights)

Wearable Sensor-Based Hip Moment Prediction

- User-specific machine learning models predicted hip torque for varying anticipation times with an average MAE ranging from 0.06 Nm/kg (0 ms anticipation) to 0.11 Nm/kg (250 ms anticipation).
- Feature selection for each anticipation time showed that EMG was more useful for predicting with anticipation times within 150 ms, which may be driven by the electromechanical delay of muscles.



Model Prediction Performance based on Ambulation Mode and Anticipation Time



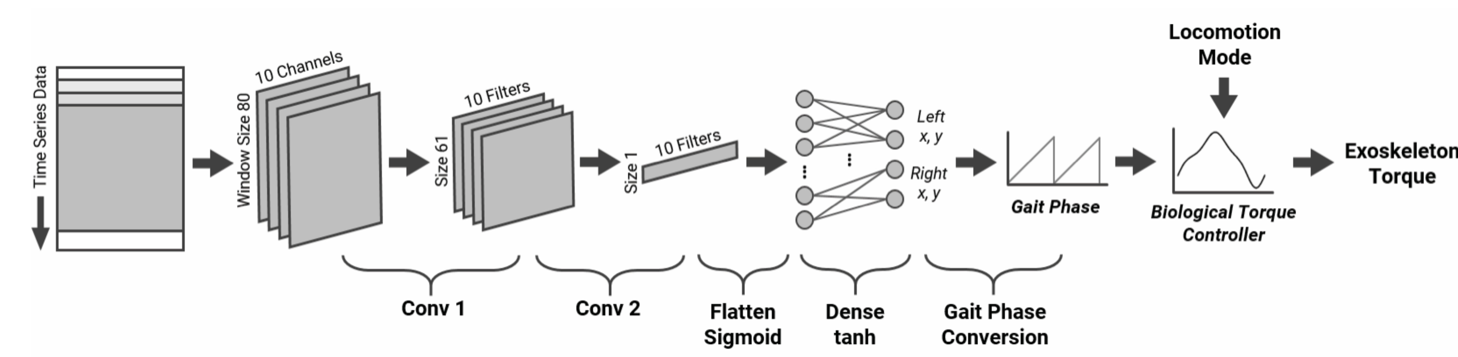
Sensor Type Selection based on Ambulation Mode and Anticipation Time

Robust Prediction of User-state Variables

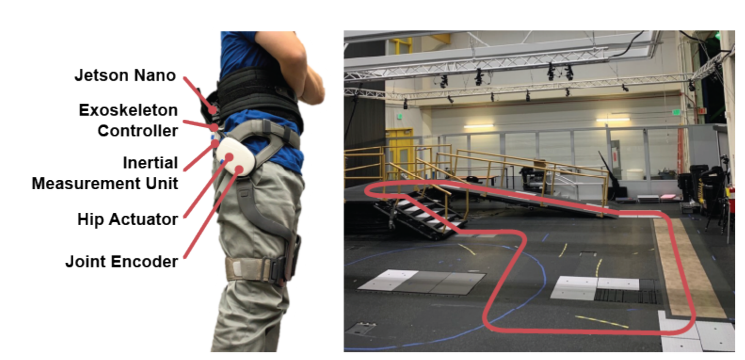
- Robust estimation of different user state information is critical feature for controlling exoskeletons to provide an effective joint assistance.
- Ground slope influences the user's biological demand indicating a need for a change in exoskeleton assistance level (Lee, RAL 2021 – Under Review).
- Gait phase variable dictates the user's movement during locomotion which is directly correlated with the exoskeleton assistance timing (Kang, RAL 2021).

Locomotion Mode Independent Gait Phase Estimation

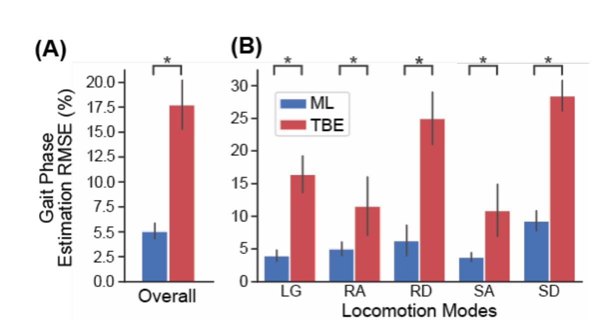
- Utilizes convolutional neural network to extract mechanical sensor information (encoder and IMU) from the exoskeleton device to estimated the user's locomotion mode (level ground, ramp as/descent, and stair as/descent).
- Overall ML model performance had an overall estimation RMS error of 5% beating the convolutional analytical method (using a foot switch) by 67%.



Locomotion Mode Independent Gait Phase Estimation Strategy using CNN



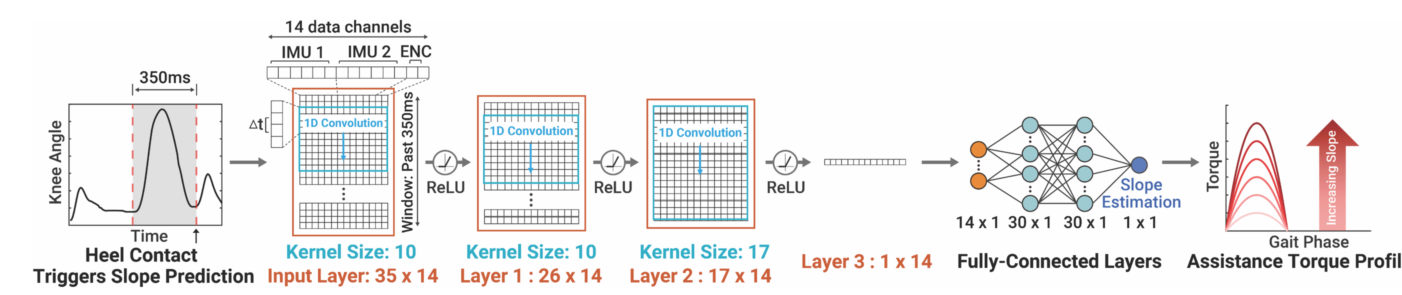
Experimental Setup for Controlling Human Subject Gait Phase Estimation Data



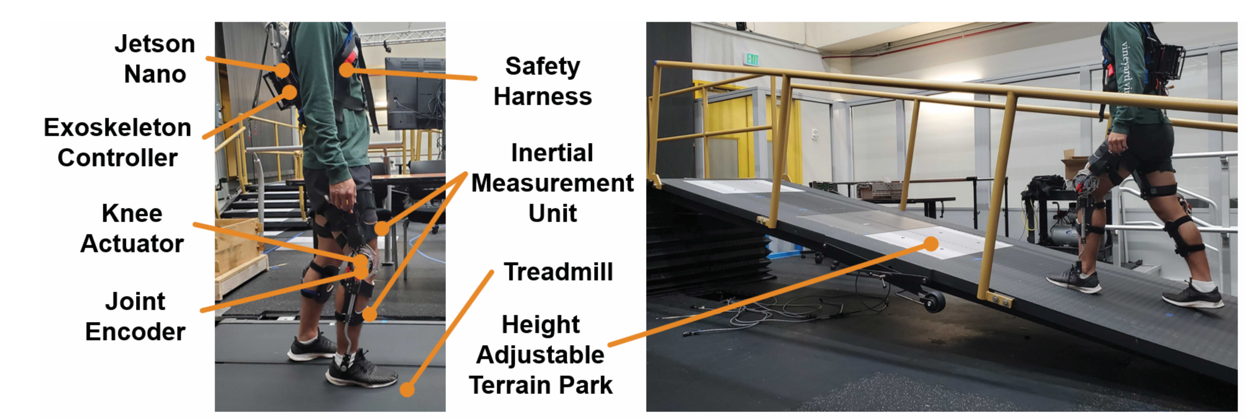
Online Validation of Gait Phase Estimator For Multimodal Locomotion

Real-Time Slope Prediction

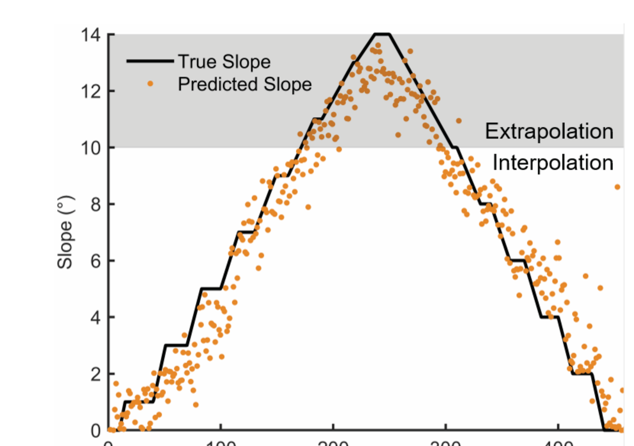
- Deep neural network uses the IMU (shank and thigh) and joint encoder data to predict the user's ground slope incline at heel contact (swing phase data) during locomotion.
- Optimized ML model was able to generalize well and predict accurately with an RMS error of 1.5° across different slope inclines (even outside the region of training data set).



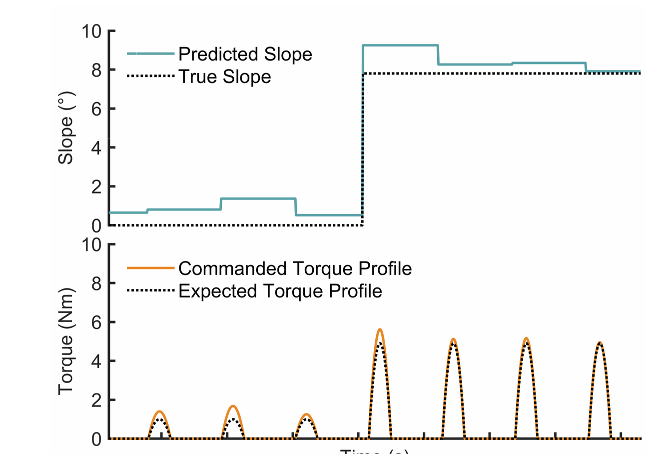
Neural Network-based Ground Slope Predictor for Modulating Knee Exoskeleton Assistance Magnitude



Experimental Setup for Controlling Human Subject Slope Prediction Data



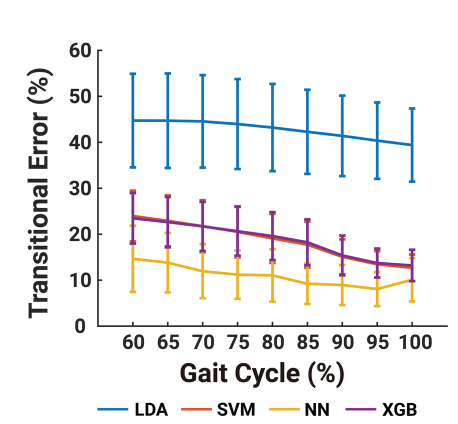
Real-Time Slope Prediction on Treadmill While Varying Slope Inclines



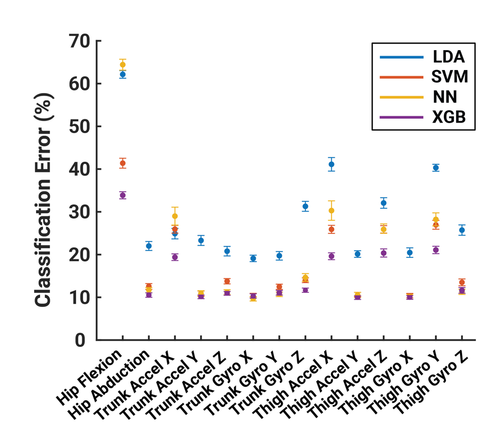
Real-Time Assistance Magnitude Modulation With Ground Slope Change

Intent Recognition using Sensor Fusion

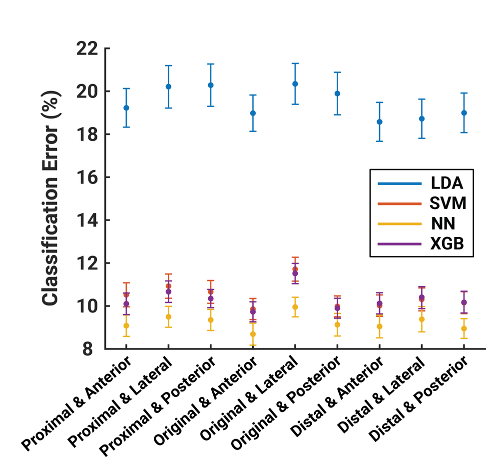
- User intent recognition such as predicting the user's locomotion mode is paramount in translating robotic exoskeleton technologies to a more realistic setting such as outdoor locomotion (Kang, Biorob 2020)
- Accurate and continuous prediction of user's locomotion mode is critical in ensuring a natural exoskeleton assistance is provided to the user (Kang 2021 – In Prep)



Transition Point Label



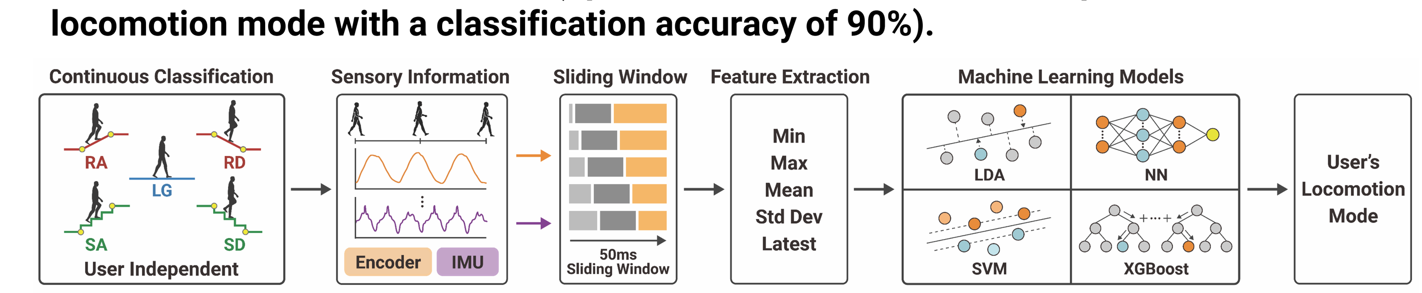
Effect of Dropping Mechanical Channel



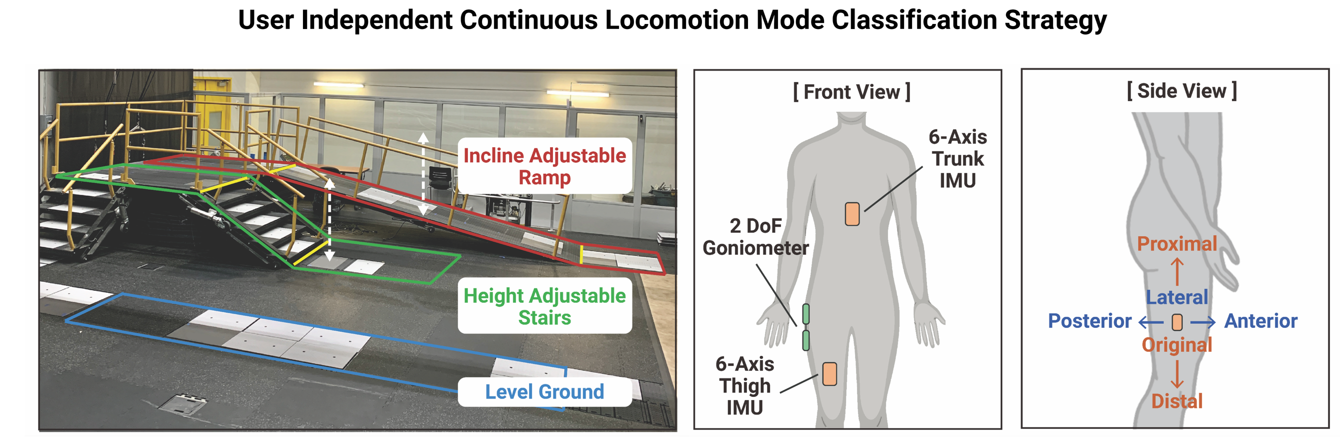
Effect of Changing IMU Location

Continuous Locomotion Mode Classification

- Comprehensive understanding of how to utilize exoskeleton's sensory information for a robust locomotion mode classification is limited.
- Study explores different ML algorithms for developing a continuous user-independent locomotion mode classification (optimized neural network model predicts the user's locomotion mode with a classification accuracy of 90%).



User Independent Continuous Locomotion Mode Classification Strategy



Experimental Setup for Controlling Human Subject Locomotion Data