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

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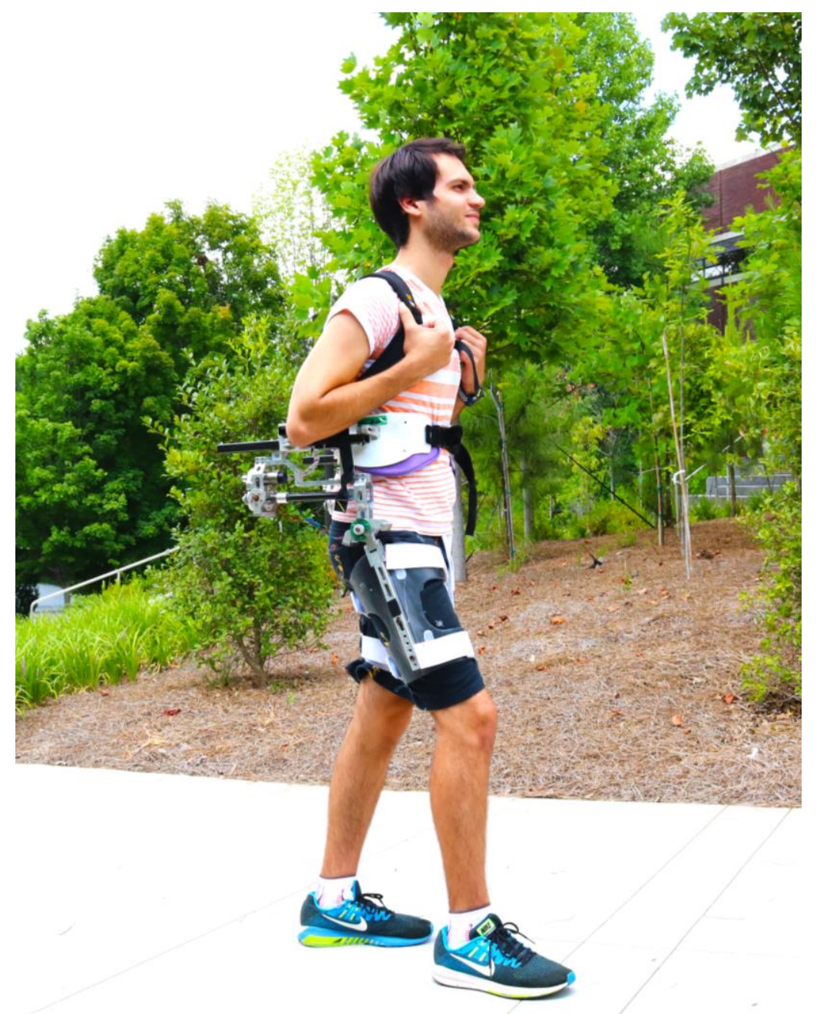
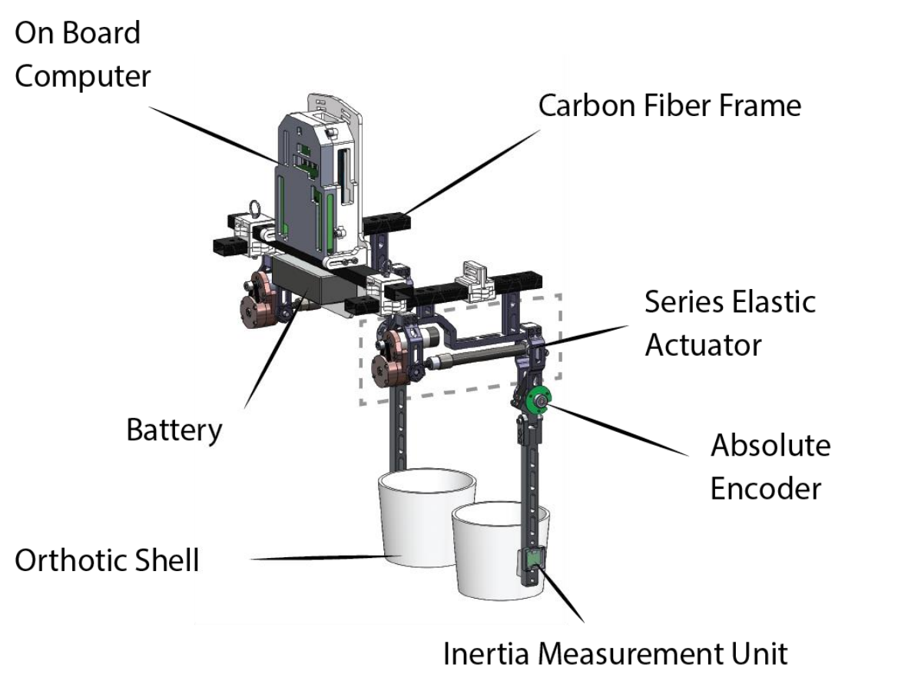
Powered Hip Exoskeleton

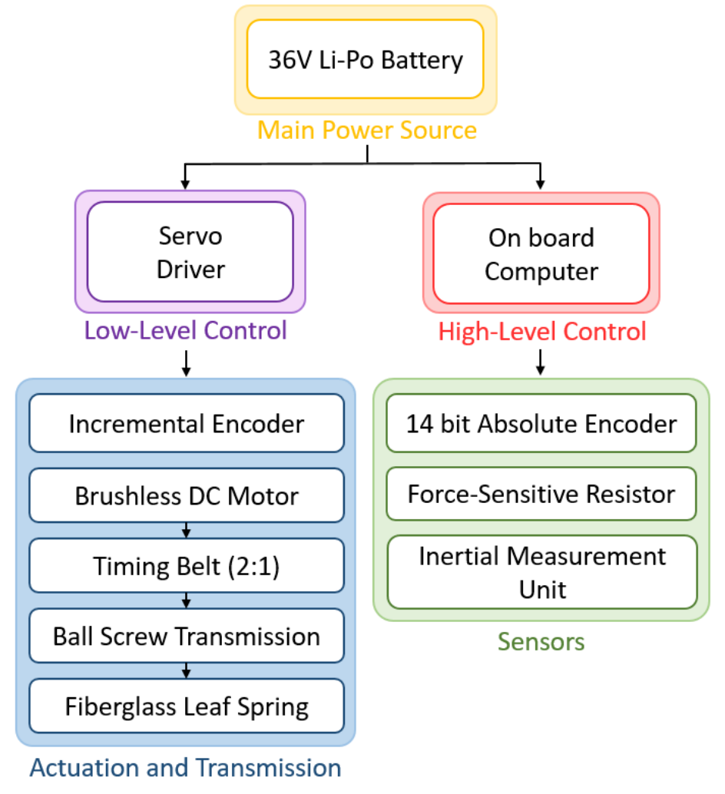


- Human hip augmentation is both novel and provides a theoretically high value proposition
- Myoelectric sensing integration in exoskeleton control may provide the needed biological catalyst to enable assistance during dynamic locomotion
- Novel controller with highly robust intent recognition enables seamless exoskeleton control for variety of activities
- More real-world biomechanical testing is needed for evaluating the exoskeleton performance in human augmentation

Exoskeleton Specification
DOF: Flexion/Extension, Ab/Adduction
ROM: 100° Flexion / 30° Extension
Peak Torque: ~ 60 Nm
Max Continuous Torque: ~ 30 Nm
Max Speed: ~ 3 rad/sec
Torque Bandwidth: 5 Hz
Actuator Weight: 1.5 kg
Total Device Weight (with Battery): 7 kg

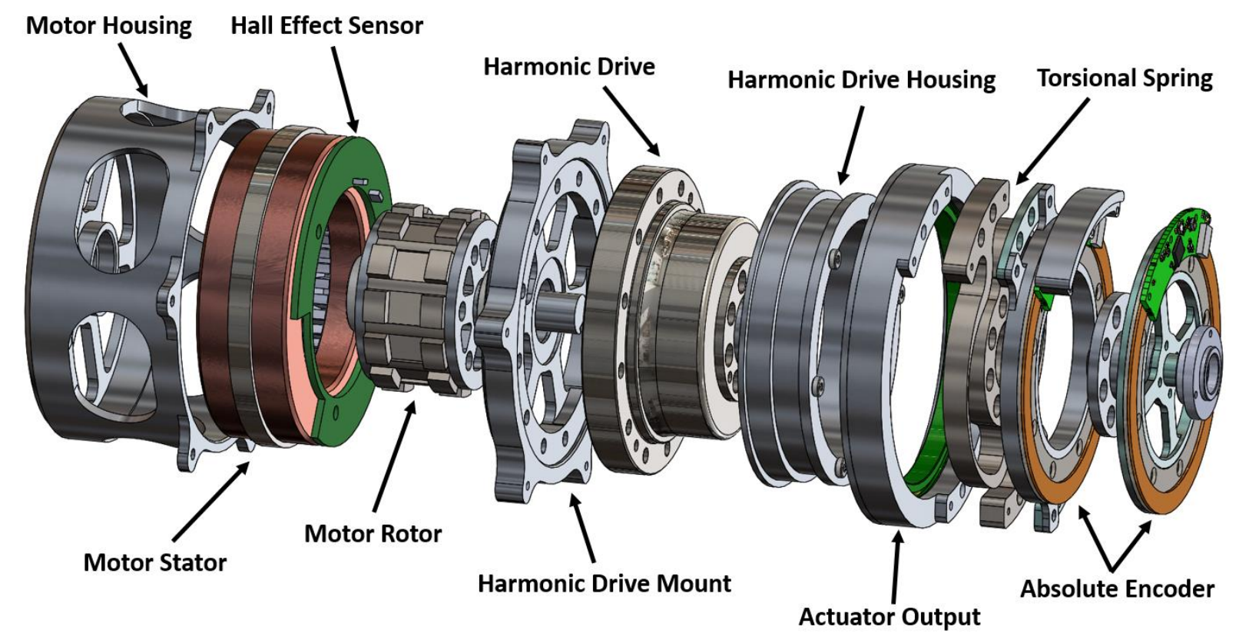


Exoskeleton mechanical design



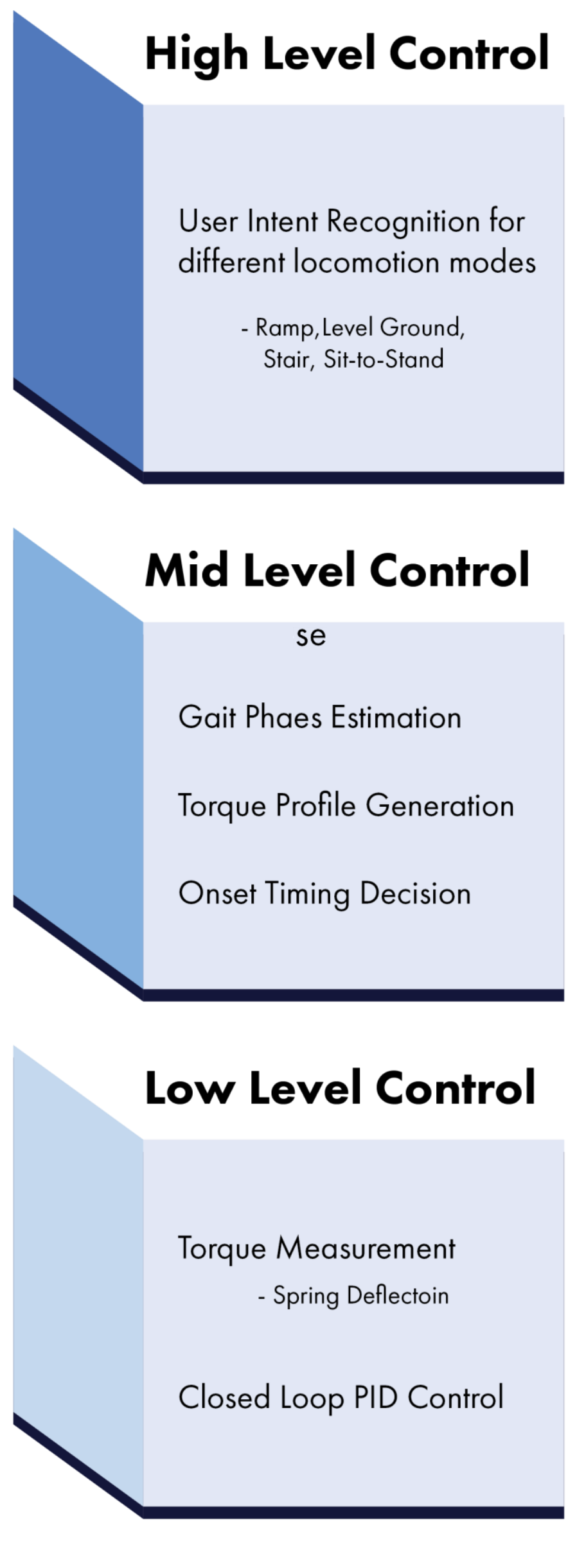
36V Li-Po Battery
Main Power Source
Servo Driver
Low-Level Control
On board Computer
High-Level Control
Incremental Encoder
Brushless DC Motor
Timing Belt (2:1)
Ball Screw Transmission
Fiberglass Leaf Spring
Actuation and Transmission
14 bit Absolute Encoder
Force-Sensitive Resistor
Inertial Measurement Unit
Sensors

System Architecture



Harmonic drive based series elastic actuator

Exoskeleton Control Strategy



High Level Control
User Intent Recognition for different locomotion modes
- Ramp, Level Ground, Stair, Sit-to-Stand

Mid Level Control
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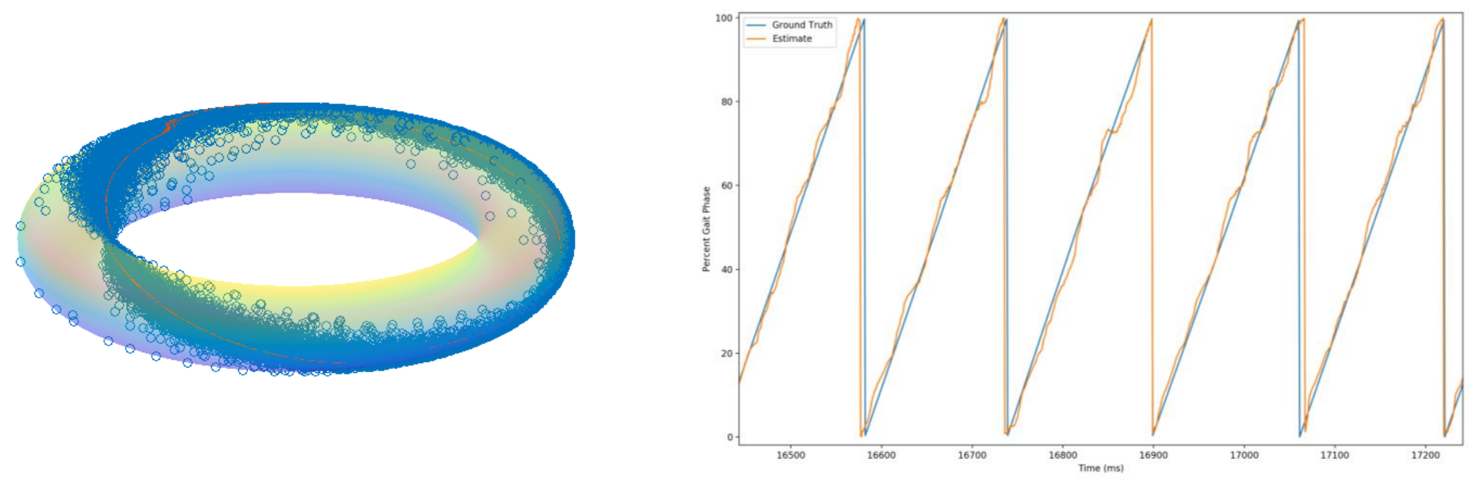
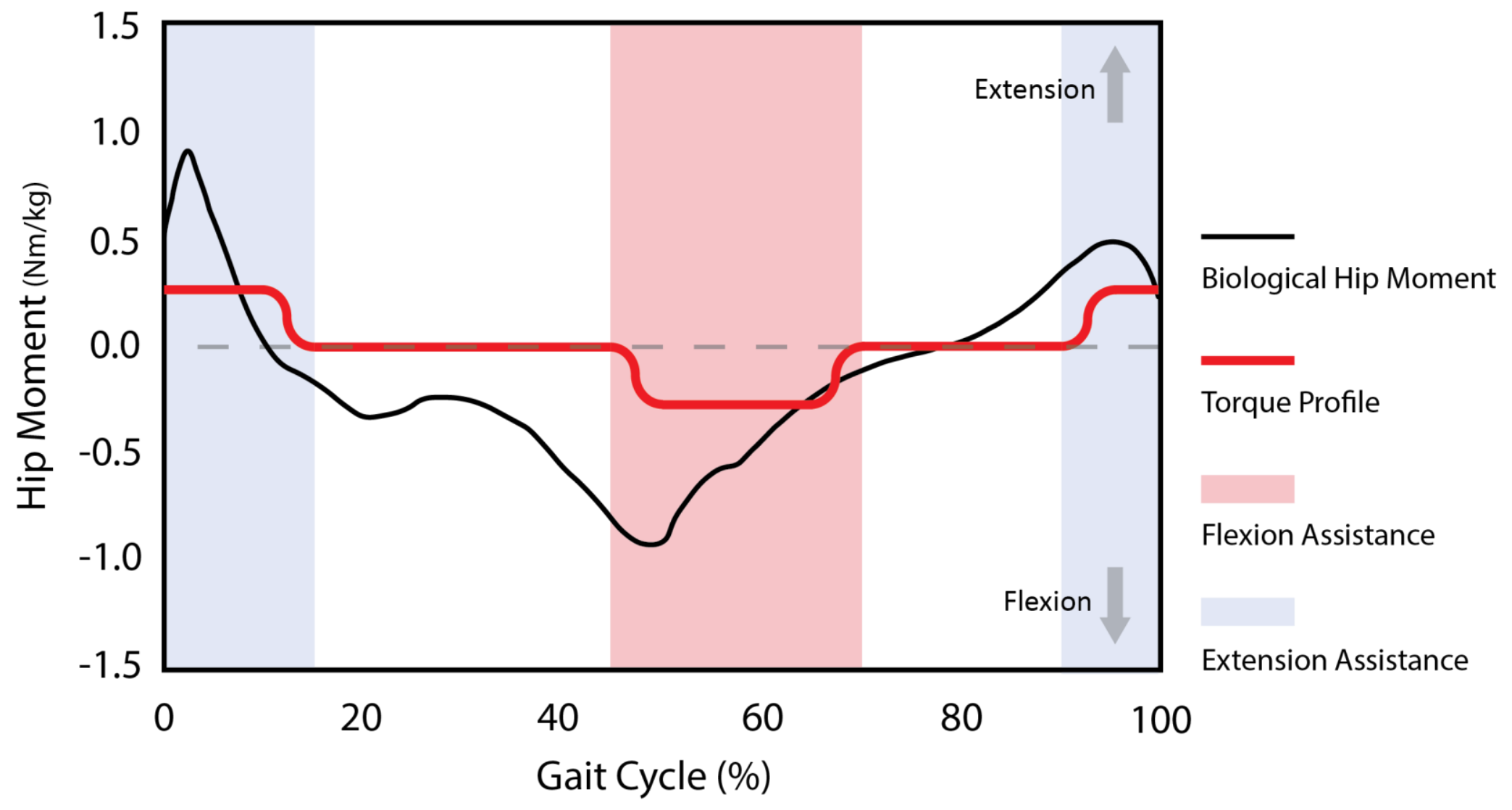
Gait Phaes Estimation
Torque Profile Generation
Onset Timing Decision

Low Level Control
Torque Measurement
- Spring Deflectoin
Closed Loop PID Control

Three Tier Control Approach

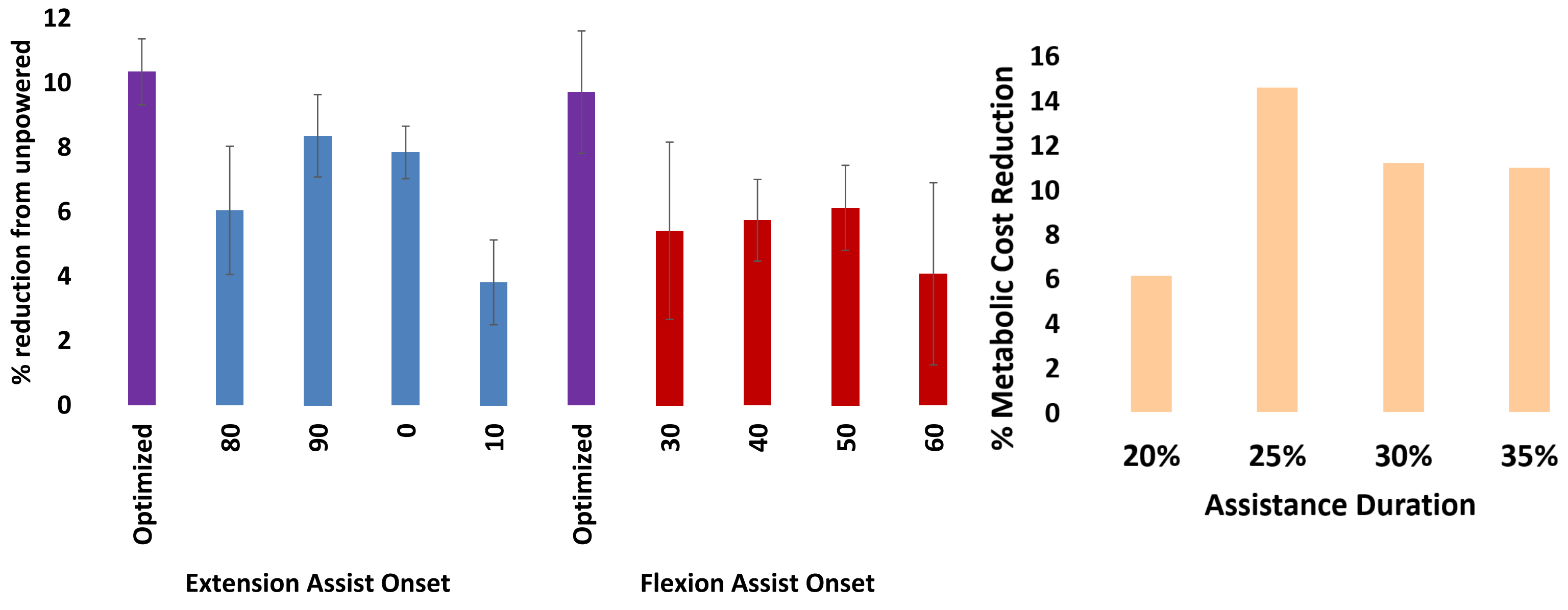


Gait Phase Estimator using Machine Learning

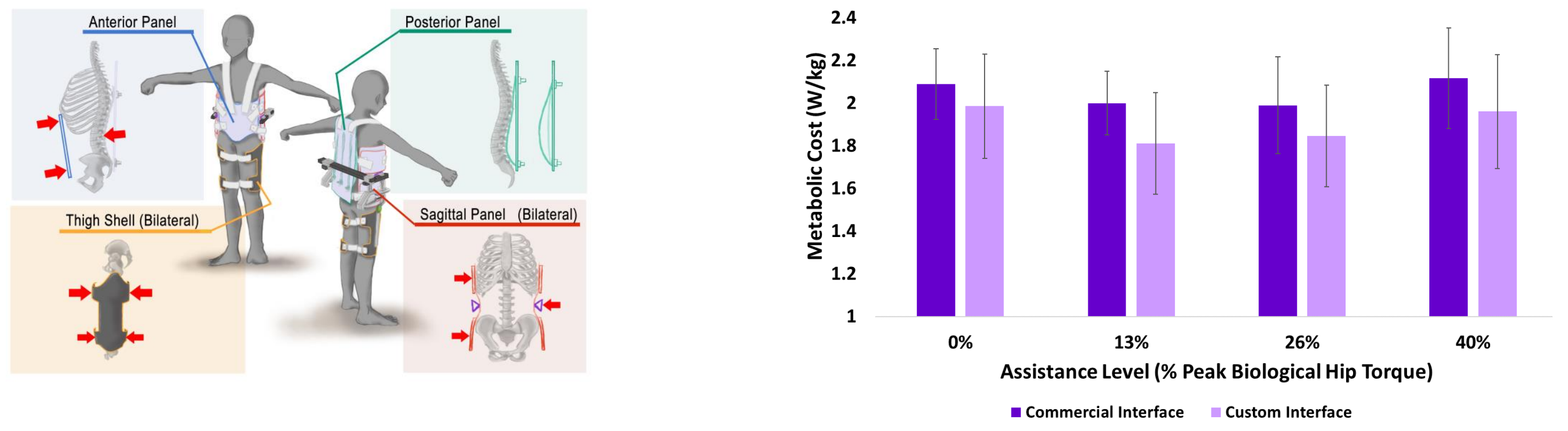


Biological Torque Control Profile

Prior work: Exoskeleton Performance Validation

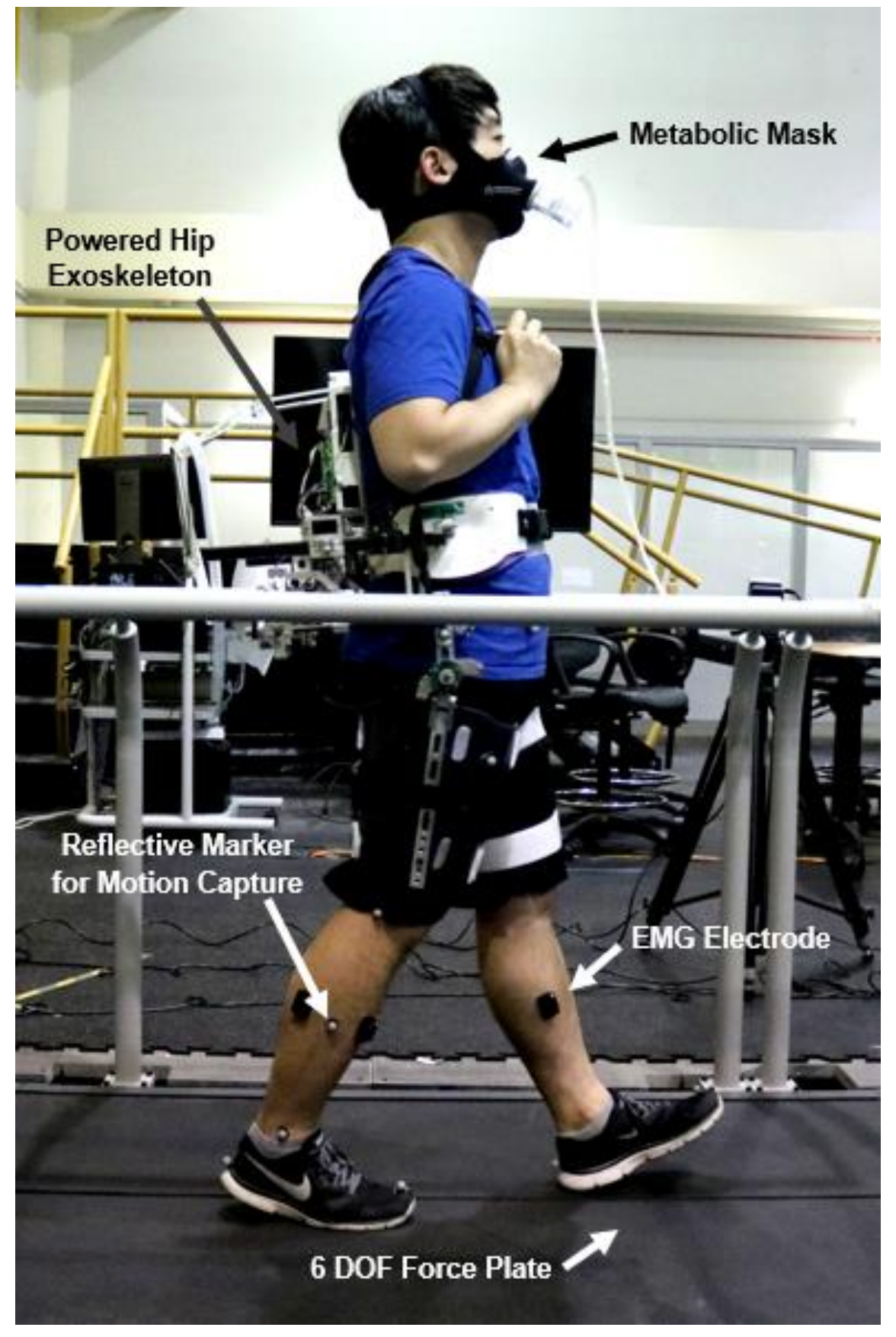


Metabolic Cost Results with Different Onset Timing and Duration



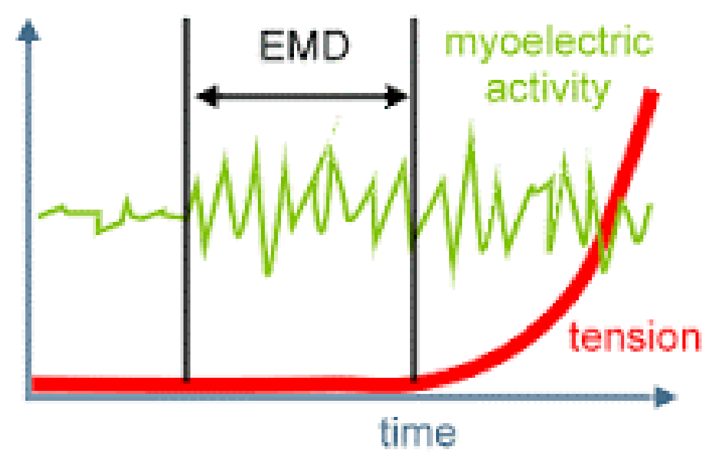
Metabolic Cost Results as a function of interface and level of assistance

Myoelectric Based Control Approach



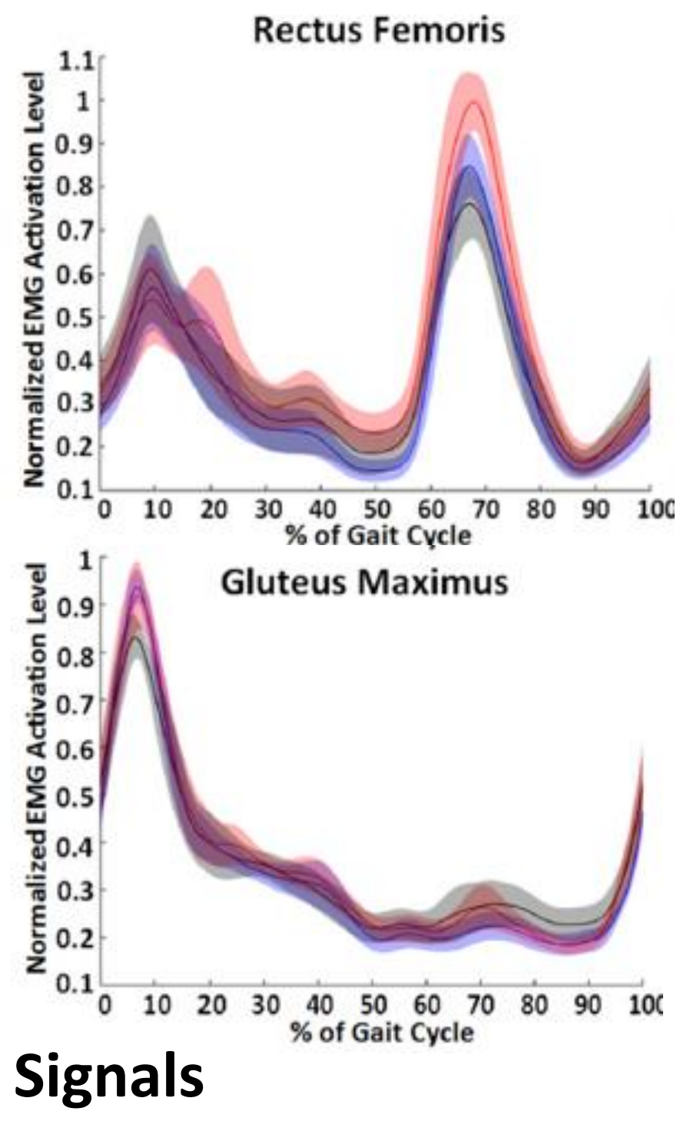
Objective 1: Determine the most effective strategy of providing exoskeleton hip assistance for reducing metabolic cost using a novel myoelectric controller

- Conventional proportional EMG signal driven controllers have limitations
- Prior exoskeleton studies showed that multiple assistance control parameters (magnitude and timing) contribute to exoskeleton performance
- Sensor fusion approach of utilizing both mechanical and EMG sensors may provide optimal exoskeleton assistance level

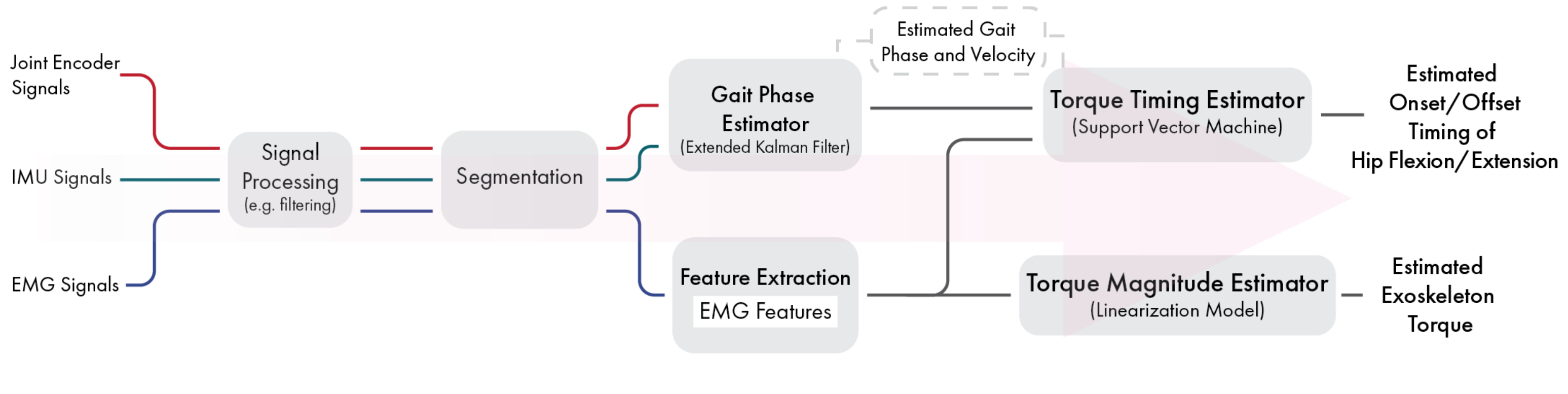


Electromechanical Delay

E-tattoo



Exoskeleton Control using Myoelectric Signals



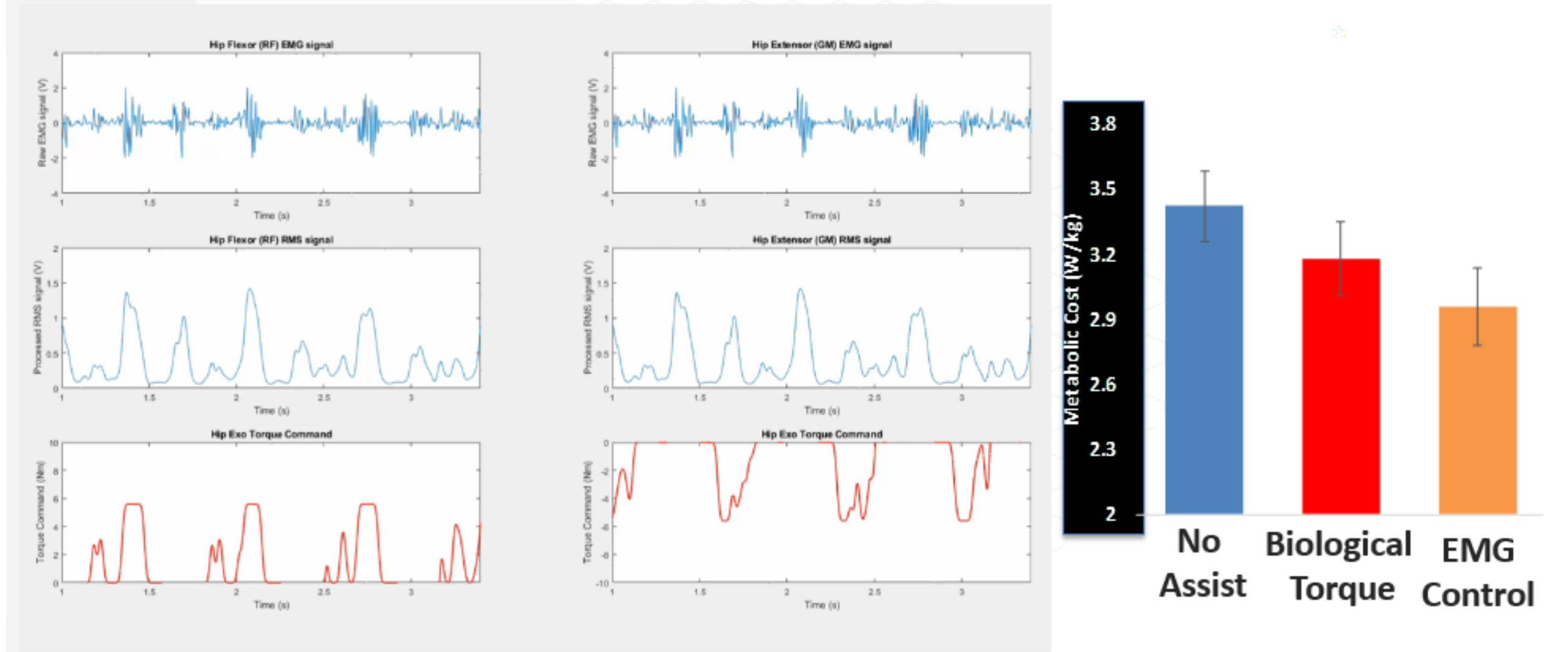
Joint Encoder Signals
IMU Signals
EMG Signals
Signal Processing (e.g. filtering)
Segmentation
Gait Phase Estimator (Extended Kalman Filter)
Feature Extraction
EMG Features
Estimated Gait Phase and Velocity
Torque Timing Estimator (Support Vector Machine)
Torque Magnitude Estimator (Linearization Model)
Estimated Onset/Offset Timing of Hip Flexion/Extension
Estimated Exoskeleton Torque

Sensor fusion strategy to control the hip exoskeleton

EMG Controller Performance Comparison

Objective 2: Compare the metabolic and biomechanical effects of a novel controller driven by myoelectric inputs vs a standard controller driven by kinematic inputs

- Current state-of-the-art controllers (e.g. impedance) use kinematic inputs to control a kinematic or kinetic profile
- Aim to directly compare the biomechanical and energetic changes with a novel myoelectric controller compared to standard controller
- Hypothesis is that EMG control performs better on dynamic (speed and incline varying tasks) tasks

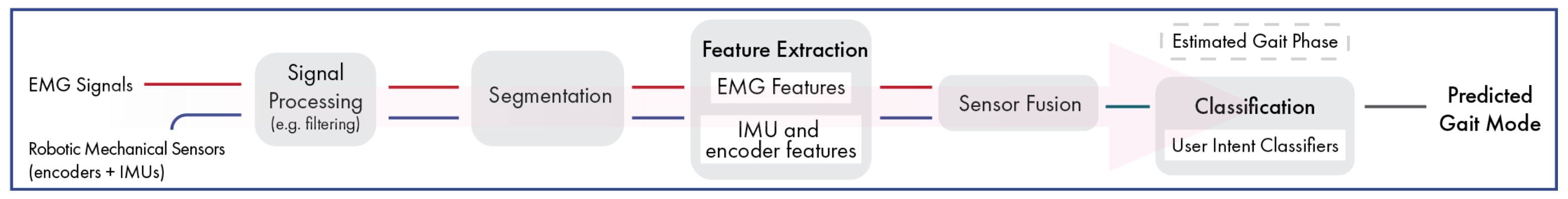


Proportional Myoelectric Control improves outcomes

Intent Recognition using Myoelectric Sensor Fusion

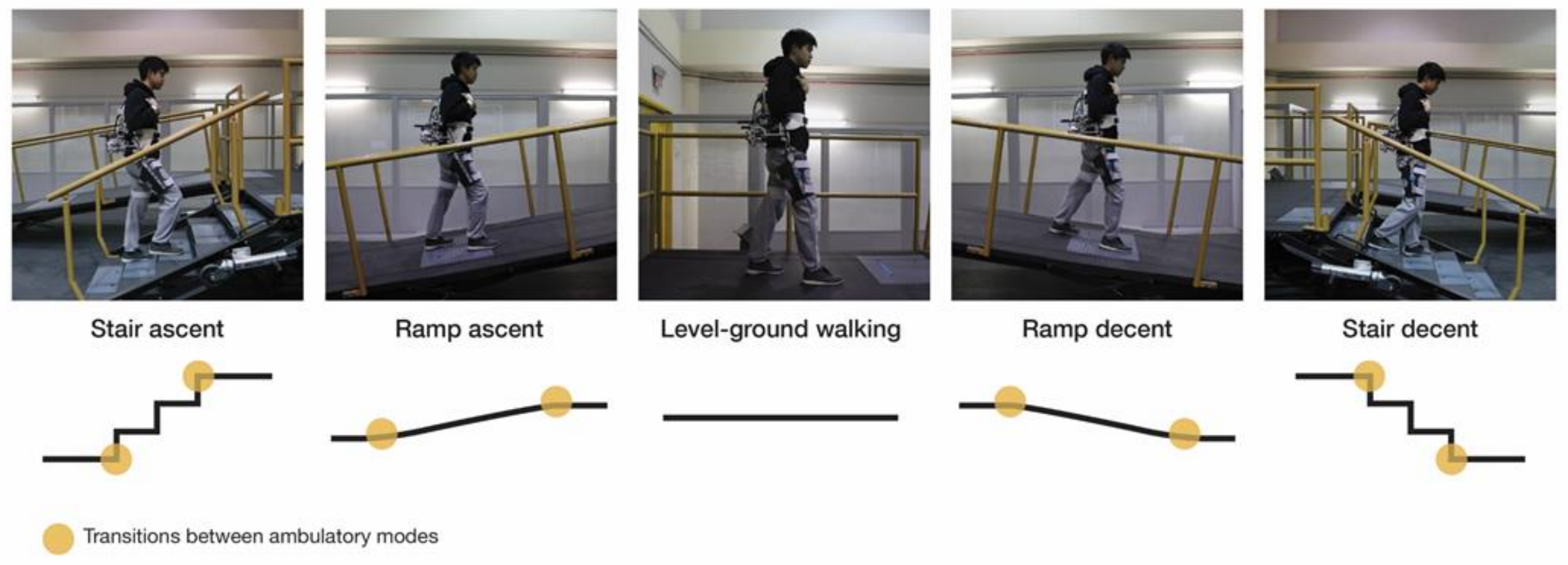
Objective 3: Determine the contributions of high-level intent recognition using myoelectric information to improve control of a powered hip exoskeleton over simulated community terrain

- High level intent recognition is needed to provide adaptive exoskeleton assistance to a variety of locomotion tasks encountered in the community
- Myoelectric signals and robotic sensor data will be used with machine learning techniques to improve the speed and accuracy of an intent recognition system

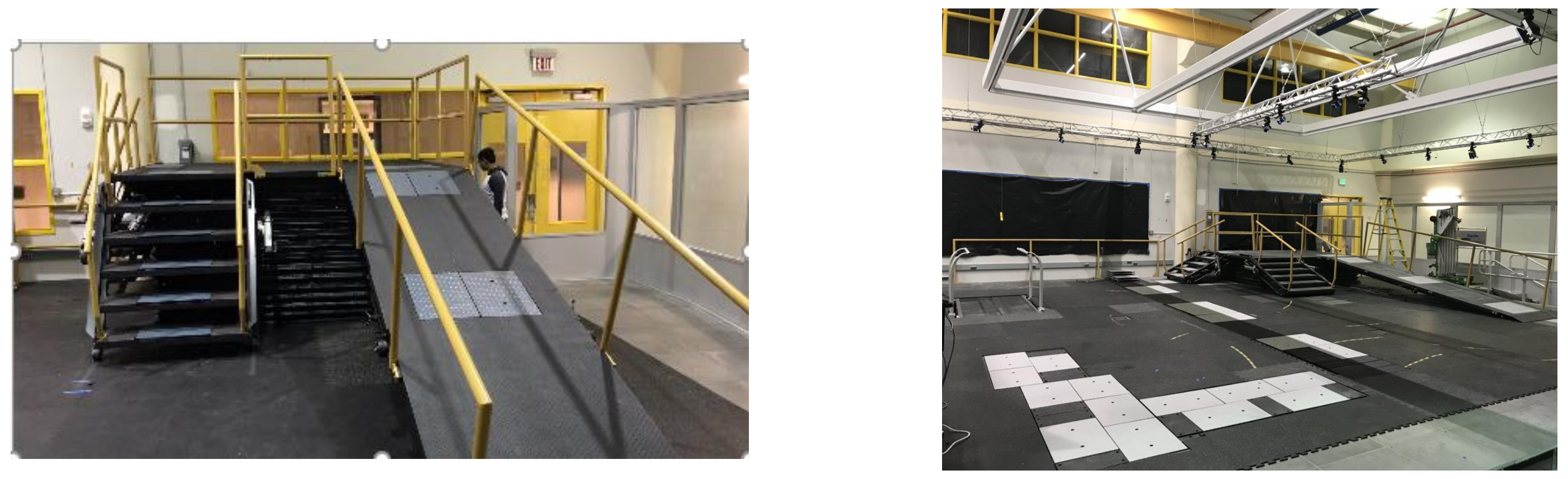


EMG Signals
Robotic Mechanical Sensors (encoders + IMUs)
Signal Processing (e.g. filtering)
Segmentation
Feature Extraction
EMG Features
IMU and encoder features
Sensor Fusion
Estimated Gait Phase
Classification
User Intent Classifiers
Predicted Gait Mode

User intent recognition strategy for locomotion mode classification



Autonomous over-ground exoskeleton testing



Experimental area capable of simulating different locomotion modes