NRI: INT: COLLAB: Accelerating Large-Scale Adoption of Robotic Lower-Limb Prostheses through Personalized Prosthesis Controller Adaptation

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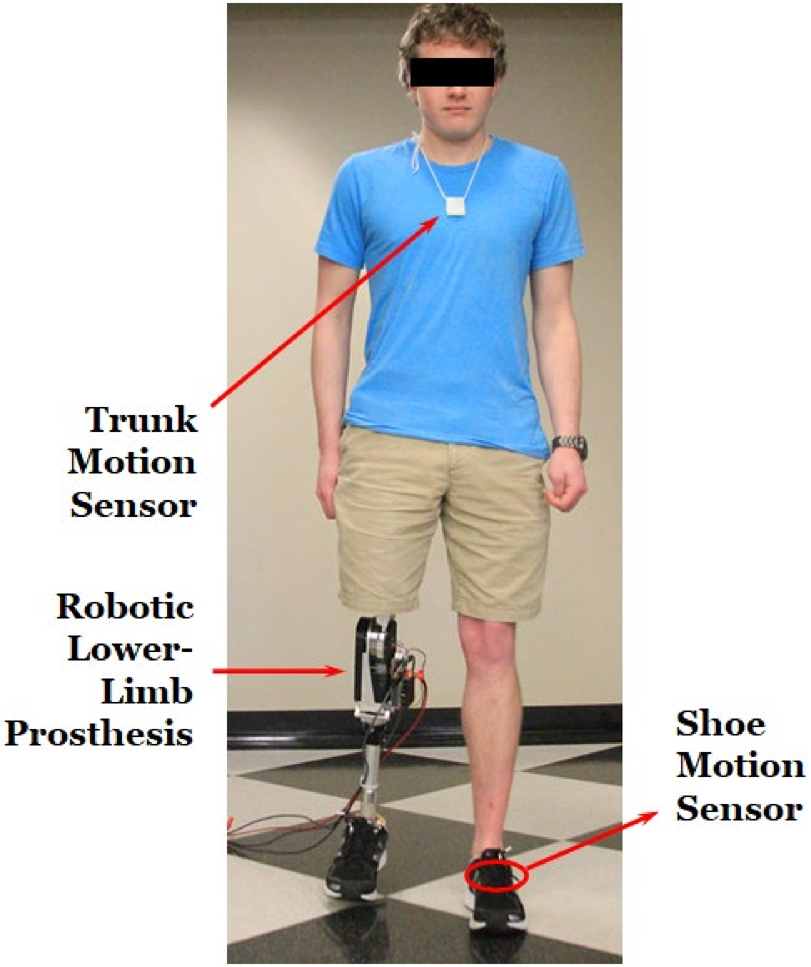
Robotic Lower-Limb Prostheses: Great Potential but Difficult to Tune

- Traditional passive prostheses lack the capability of generating joint power and thus are unable to restore normal walking gait.
  - Problems include asymmetric gait, greater energy consumption, higher hip torque/power, and inability to assist power-demanding locomotive functions (such as upslope walking and stair ascent).
- Robotic lower-limb prostheses (RLLPs) represent a fundamental change in energetic behavior and provide the potential to significantly improve the mobility of the amputee users.

- However, as smart wearable robots, RLLPs require frequent adjustments of numerous control parameters for personalized fitting, placing a heavy burden to the amputee users.
- **<u>Personalized Prosthesis Controller Adaptation (PPCA)</u>**: Automating Controller Tuning and Intent Recognizer Retraining to Accelerate Large-Scale Adoption of RLLPs

Research Overview: Automatic Tuning of Prosthesis Controller and Intent Recognizer with Global Sensing

- Human gait in locomotion is a form of full-body dynamics, not just leg and foot. This is especially important for robotic prosthesis-aided amputee gait, in which prosthesis action directly affects the full-body movement.
- In the PPCA, the prosthesis tuning is conducted based on the sensor inputs reflecting full-body movement, including the upper body movement and contralateral (healthy) leg movement.
  - #1) Fundamental studies on robotic prosthesis-assisted walking and prosthetist-conducted controller tuning.
  - #2) Wearable sensor development.
  - #3) Automatic tuning of prosthesis motion controller.
  - #4) Quasi-supervised adaptation of the intent recognizer in the prosthesis control system.



#1A: Biomechanical Study on Gait Quality under Systematic Joint Constraints

Four systematic constraints applied during experiment.

A. baseline condition with no constraints.
B. ankle constraint
C. knee constraint
D. knee+ankle constraints

Our Gait Quality Metrics of Study

1. **POGS: Prosthetic Observational Gait Score** which is scored visually by a clinician on a scale of 0-32 (lower is better).
2. **GDI: Gait Deviation Index** based on 3D kinematics of lower limb with scores ≥ 100 indicative of normal gait
3. **Impulse Asymmetry -** the absolute value difference in impulse between limbs
4. **Lateral Sway -** the difference in the max and min mediolateral trajectory of a sternal chest marker

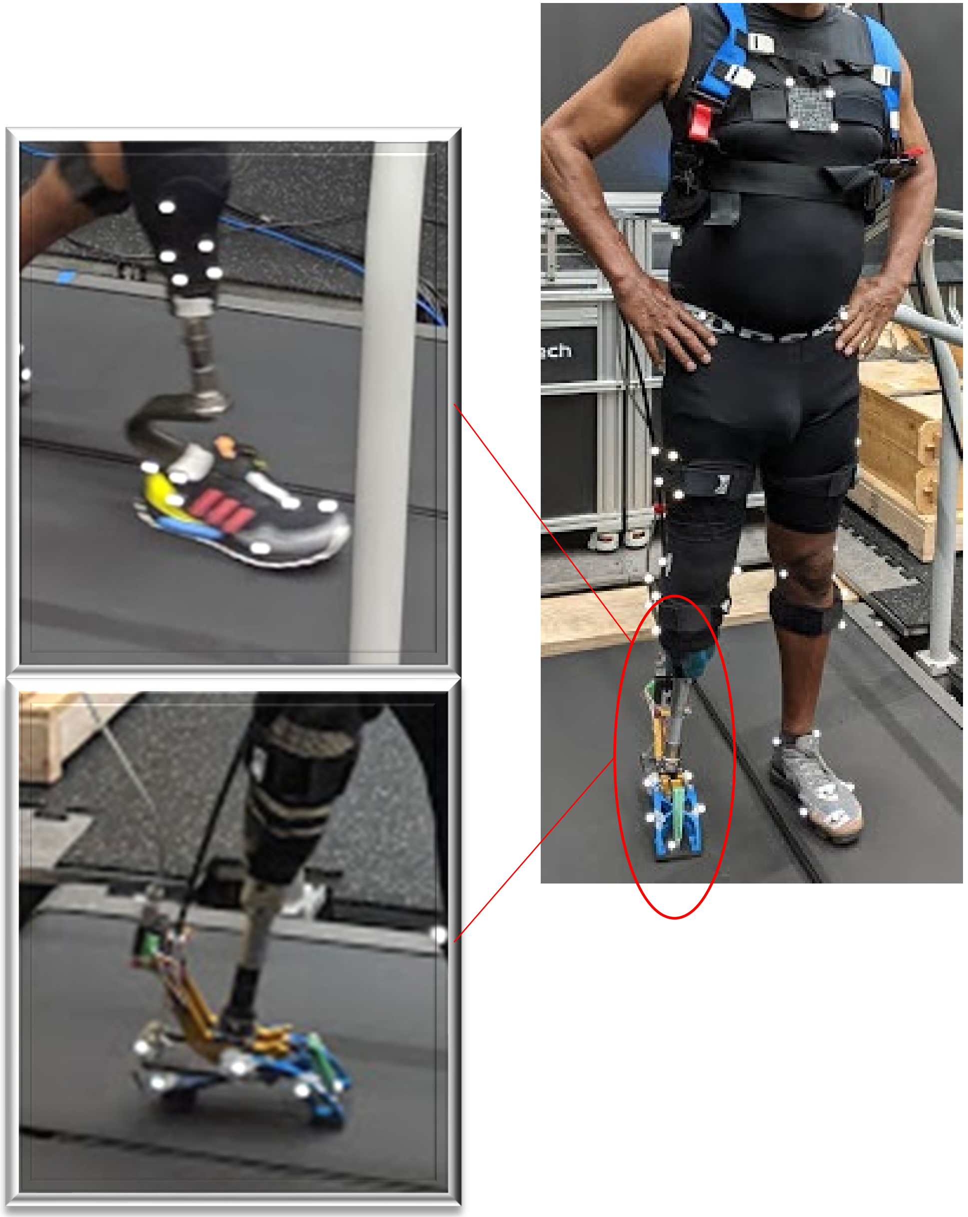
#1A: Biomechanical Study on Gait Quality under Systematic Joint Constraints **- Results**

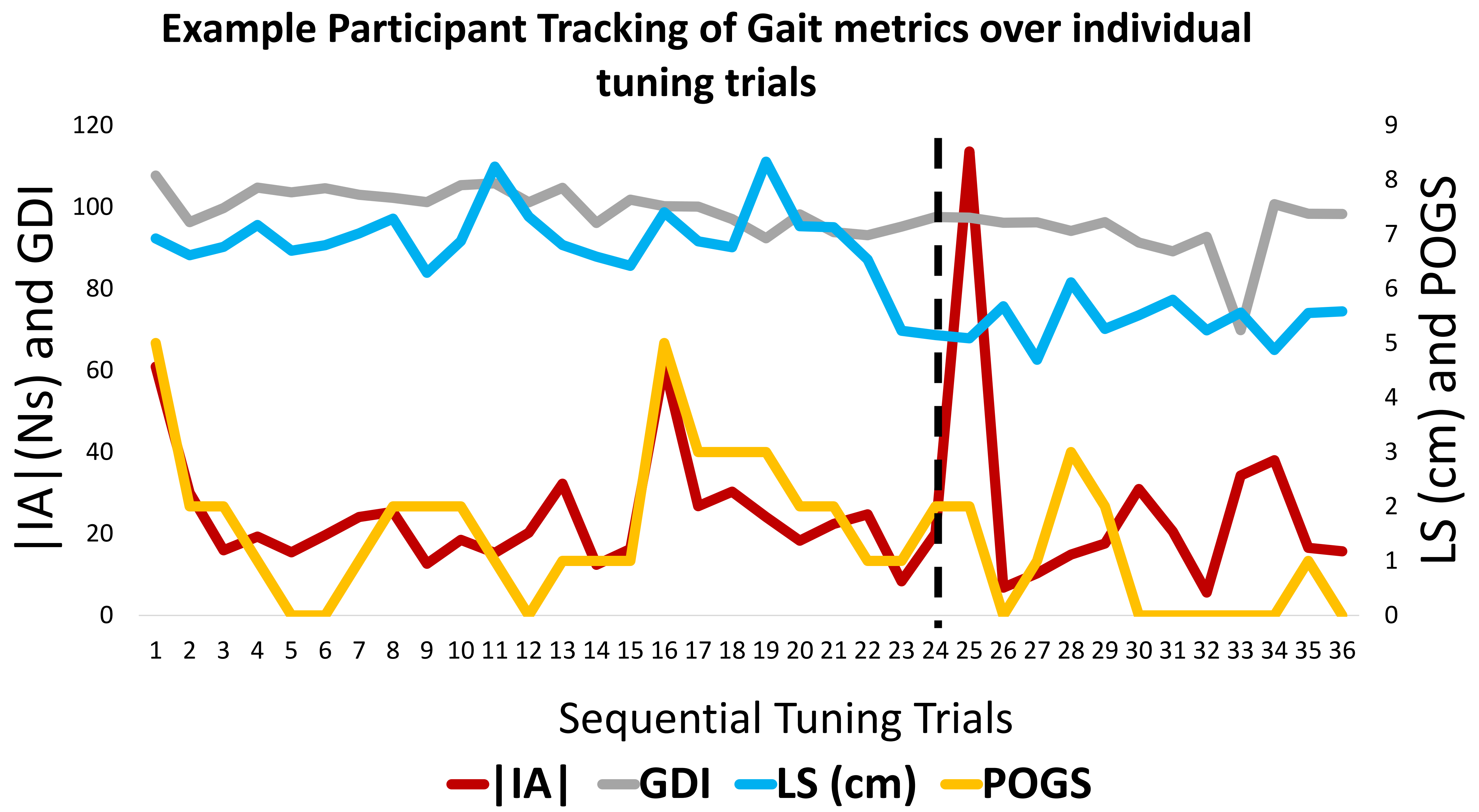
	Conditions Compared									
	Joint Constraint Comparisons						Speed Comparisons			
Gait Metrics	Baseline vs. Ankle	Baseline vs. Knee	Baseline vs. Knee+ Ankle	Ankle vs. Knee	Ankle vs. Knee+ Ankle	Knee vs. Knee+ Ankle	0.7 m/s vs. 0.85 m/s	0.7 m/s vs. 1.0 m/s	0.85 m/s vs 1.0 m/s	General Gait Deficit Sensitivity Score
Lateral Sway	0.186	0.017*	0.008*	0.053	0.004*	1	0.006*	0.002*	0.126	5
GDI	p<0.05*	p<0.05*	p<0.05*	0.351	0.022*	1	0.207	0.207	0.207	4
POGS	0.075	p<0.001*	0.001*	0.002*	0.002*	1	0.234	0.234	0.234	4
Impulse Asymmetry	0.565	0.23	0.002*	0.466	0.014*	0.019*	0.427	0.427	0.427	3

Herrin et al. in prep.

#1B: Prosthetist-Conducted Controller Tuning and Gait Quality Assessment

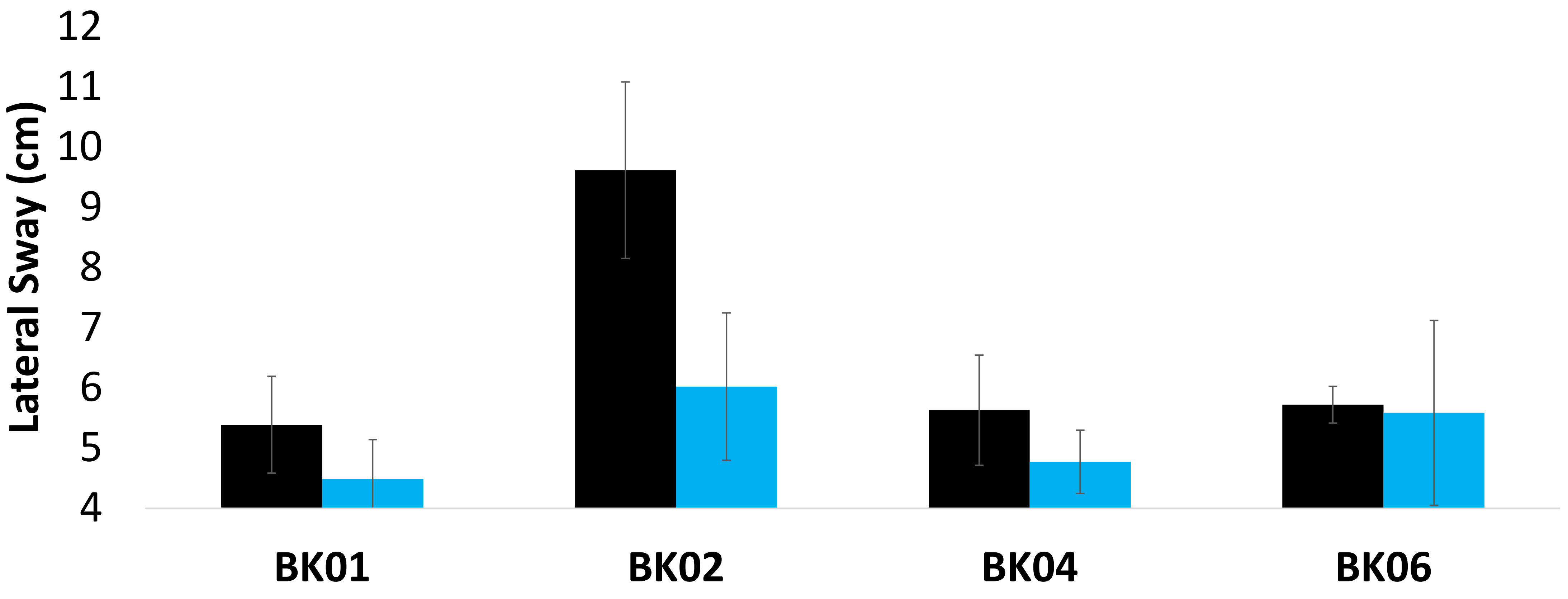
- N=7 individuals with below-the-knee amputation walked on their clinically prescribed passive foot and a robotic powered prosthesis while we collected lower limb and trunk biomechanics
- The robotic powered prosthesis (Humotech PRO-001) was tuned by a prosthetist according to standard clinical practices (i.e. observational gait analysis and patient feedback)
- We analyzed 4 common gait quality metrics post-hoc over each tuning trial to better understand gait quality changes over the tuning process and compared the passive and tuned gait metrics
- Two sample t-tests were used to compare differences between passive and tuned powered foot conditions with significance set at alpha <0.05





Example Participant Tracking of Gait metrics over individual tuning trials
|IA| (Ns) and GDI
LS (cm) and POGS
0
20
40
60
80
100
120
0
1
2
3
4
5
6
7
8
9
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36
Sequential Tuning Trials
|IA|
GDI
LS (cm)
POGS

Lateral Sway metric could differentiate between passive prosthesis and clinically tuned robotic prosthesis



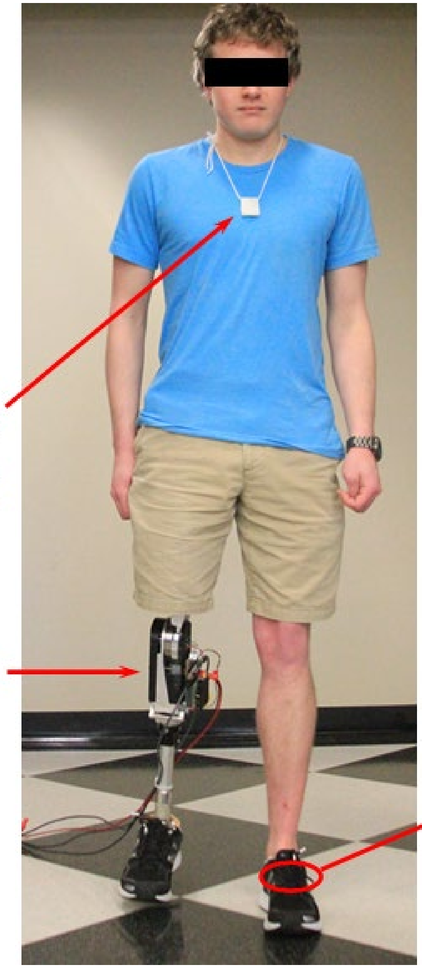
#2: Trunk Motion Sensor and Shoe/Foot Motion Sensor

- Trunk motion and shoe motion sensors are being developed by incorporating IMUs with Bluetooth wireless communication modules for real-time data collection and processing.
- The shoe sensor is especially useful (intended to be worn on the healthy-side foot), providing the detection of important gait events and supporting the recognition of the users' locomotive mode.

True Class \ Predicted Class	0	1	2	3	4	5	6	7	8
0	74.3%	11.4%	5.7%	5.7%	2.9%				
1	2.0%	87.8%	2.0%	4.1%	4.1%				
2	3.7%	3.7%	88.9%	3.7%					
3	4.3%	8.7%	13.0%	69.6%				4.3%	
4			4.6%		95.4%				
5						100.0%			
6							98.1%	1.9%	
7								100.0%	
8								0.9%	99.1%

9-class activity recognition with ***94.8% accuracy***

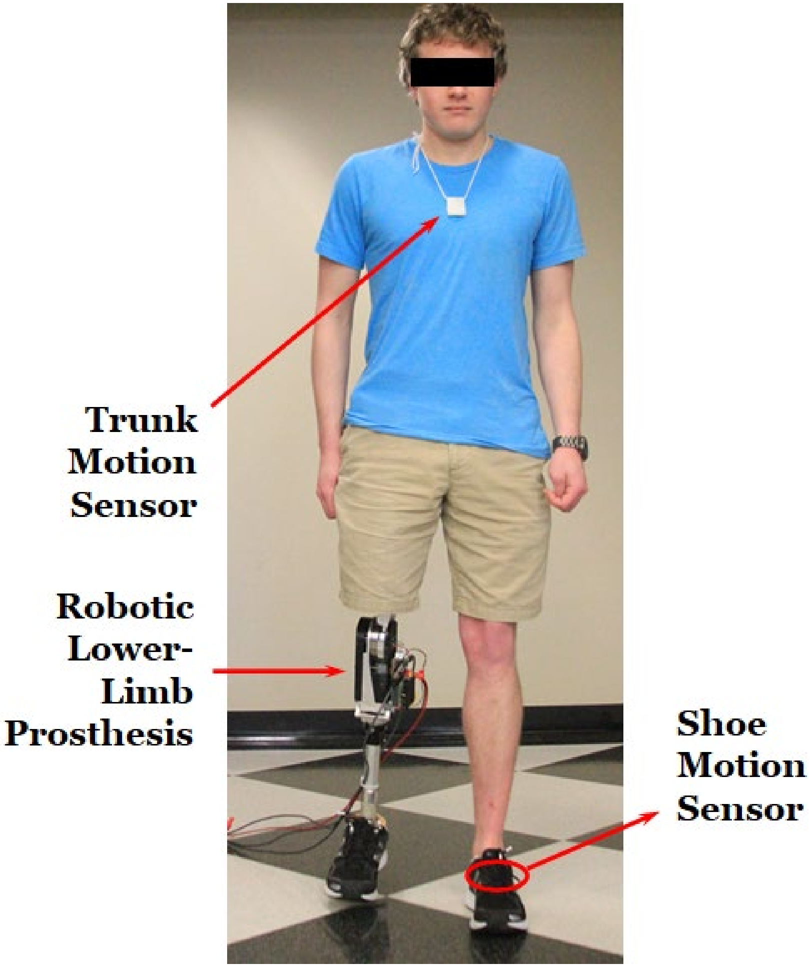
0- sitting
1- standing
2- sit to stand
3- stand to sit
4- walking
5- running
6- stair ascent
7- stair descent
8- cycling



#3: Automatic Tuning of Prosthesis Motion Controller

- Method 1: Direct-Acting Asymmetry-Based Tuning.
  - ➢ Based on the measured foot motion/force asymmetry and lateral sway, we are developing a closed-loop adaptation algorithm to regulate the dynamic behavior of the prosthetic ankle in stance (especially the push-off power).

- Method 2: Virtual Prosthetist Tuning Algorithm.
  - ➢ Emulating the decision-making process of an experienced prosthetist in tuning the controller, we are developing a multi-class SVM algorithm.
  - ➢ For each parameter, the SVM-identified class represents the adjustment action: maintain, increase/decrease slightly, or increase/decrease significantly.

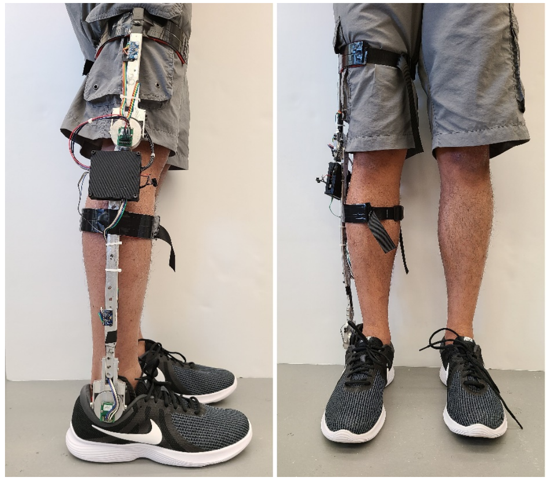


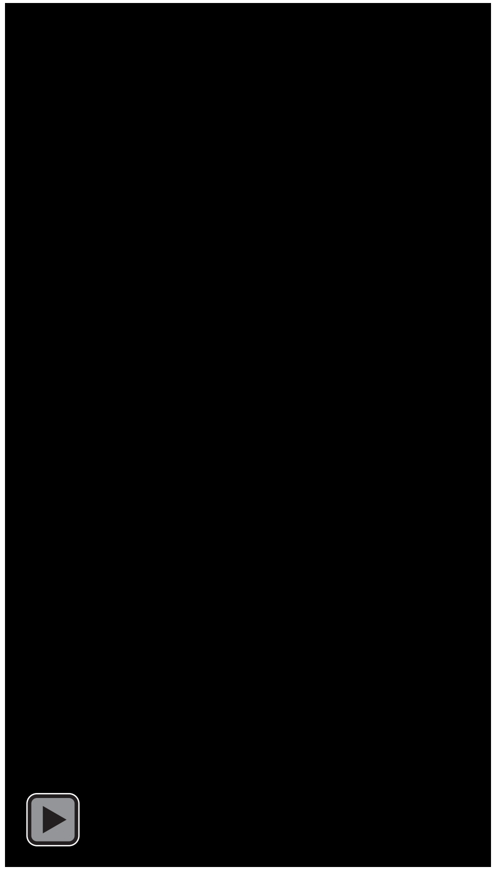
#4a: Data Collection for Intent Recognizer Adaptation

- We developed a lightweight exoskeleton-based gait data collection system to facilitate the data collection outside research labs.

- A data collection study is being conducted to create a dataset of gait data in real-world ambulation scenarios. A typical sequence in the protocol: climb up *n* flights of stairs, walk down the hallway to the other side of the building, go down *m* flights of stairs, and walk back to the original side of the building.

- Multi-modal sensors are used to create a comprehensive dataset: inertia sensors, joint goniometers, foot plantar pressure sensors, and a head-mount camera.





#4b: Quasi-Supervised Intent Recognizer Adaptation

- Signals from wearable sensors (chest and shoe) provides valuable information related to the locomotive mode and mode transition.
- Utilizing the wearable sensor signals in conjunction with the prosthesis-embedded sensor signals, we are developing a classifier with very high accuracy (Virtual Supervisor), using the method of classification with rejection.
- The Virtual Supervisor-generated training data wil be merged with existing (core) training data to retrain the intent recognizer to continuously improve its performance for each user.