Enhancing Wearable Gait Monitoring Systems: Identifying Optimal Kinematic Inputs in Typical Adolescents

Shank angular velocity & acceleration are
the most robust real-time signals from wearables
for robotic prosthetics controlled **by deep learning**

Abstract

Background - Real-time IMU gait data facilitates machine learning for control of assistive prosthetics in neurological conditions. In adolescents using wearables on different surfaces, evidence has demonstrated *spatiotemporal* differences, but there is a need to measure *signal level* differences to identify specific kinematic signals for reliable use as training inputs for a deep learning model.

Objective– To collect wearable IMU gait signals from adolescents to (1) use similarity scores to assess reliable lower limb kinematic signals and (2) identify usable signals independent of walking conditions and walking speeds.

Conclusion – To guide future machine learning models for assistive prosthetics in pediatric neurological conditions, we report the two specific raw signal kinematics in children (shank angular velocity and acceleration) that demonstrate the least variability in switching between treadmill and outdoors. Using an uncommonly large dataset for adolescents wearing IMUs, new concepts to the literature introduced here are: (a) segmented bands of similarity, (b) subject-defined similarity control group, and (c) statistical method of paired comparison to evaluate similarity scores.

Materials & Methods

PARTICIPANTS
N = 30
Ages 8–18 years old

↓

INERTIAL MOTION UNITS

4 LOCATIONS (R shank, L shank, R thigh, and L thigh)

2 KINEMATICS (acceleration and angular velocity)

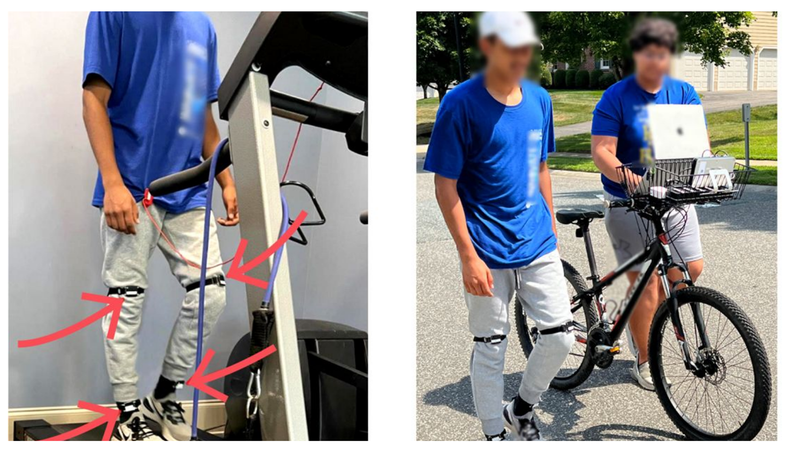
3 AXIS (AP, ML, and SI)

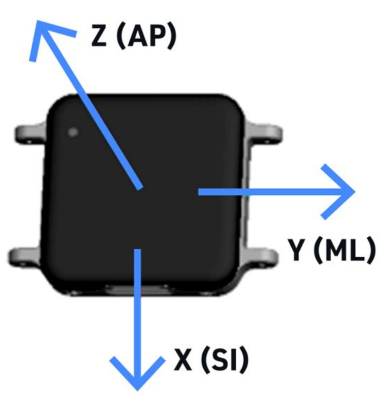
24 signals total

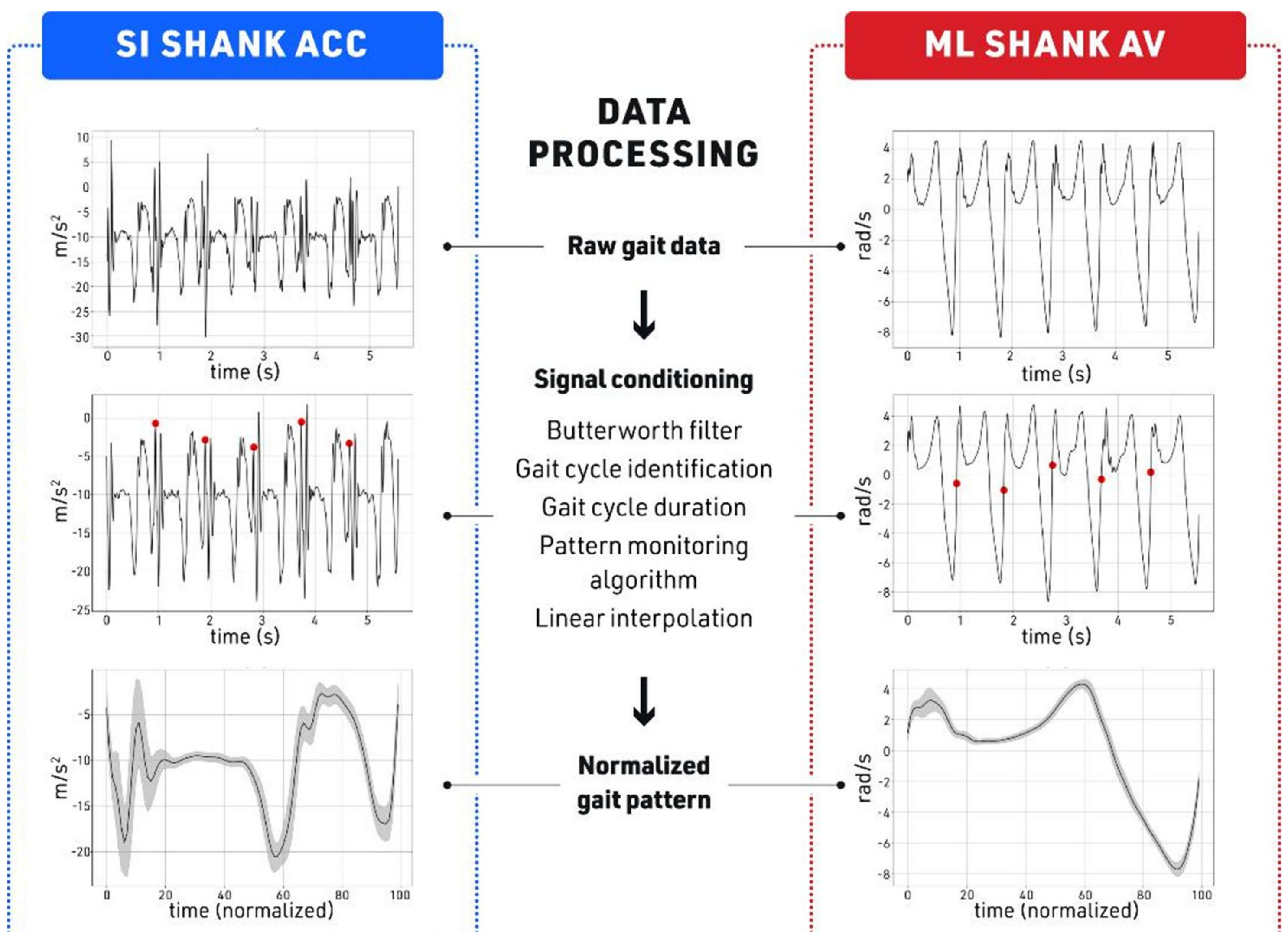
Define self-selected walking speed:
10 meter walking test (10mWT)

TREADMILL
Self-selected
Slow (+20%)
Fast (-20%)
Speed
3 minute trials
2 trials each speed

OUTDOORS
Self-selected
Slow
Fast
Speed
3 minute trials
1 trial each speed







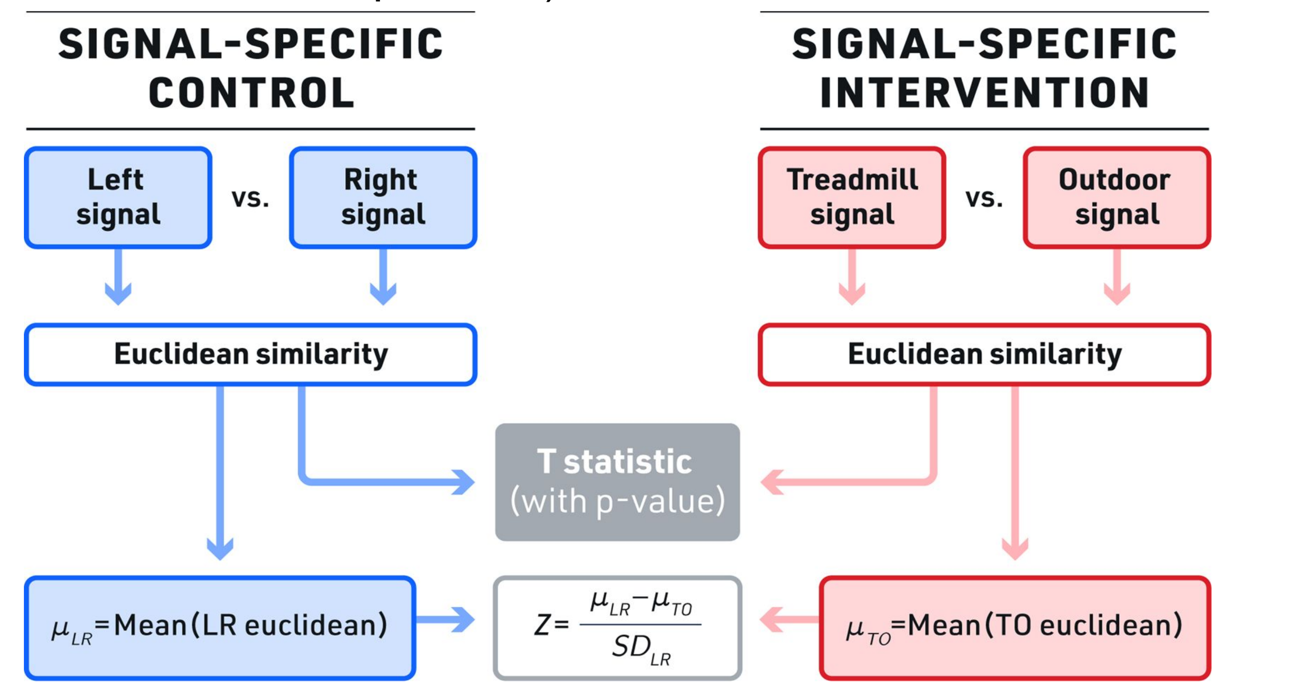
Results

Similarity scores: Two specific signals stand out in both combined & paired comparison similarity scoring:

- Acceleration X (SI axis) shank & Angular Velocity Y (ML axis) shank
- **High/middle/low similarity banding identified:**

		SELF-SELECTED				SLOW				FAST			
	Signal	cos	euc	rank	Band mean	cos	euc	rank	Band mean	cos	euc	rank	Band mean
High	SI shank Acc	0.999	0.045	1	0.997	1.000	0.032	1	0.997	0.999	0.044	1	0.998
	ML shank AV	0.999	0.047	1		0.996	0.086	4		0.999	0.040	1	
	SI thigh Acc	0.999	0.052	1		0.998	0.057	2		0.999	0.038	1	
	ML thigh AV	0.994	0.112	4		0.993	0.119	5		0.996	0.088	4	
	AP shank AV	0.993	0.116	5		0.998	0.066	2		0.996	0.091	5	
Middle	AP shank Acc	0.990	0.145	6	0.986	0.985	0.172	8	0.985	0.991	0.131	6	0.989
	AP thigh Acc	0.988	0.155	7		0.987	0.159	7		0.990	0.143	8	
	AP thigh AV	0.987	0.162	8		0.992	0.129	6		0.991	0.138	6	
	SI shank AV	0.980	0.199	9		0.974	0.227	9		0.983	0.184	9	
Low	SI thigh AV	0.972	0.236	10	0.954	0.973	0.233	10	0.961	0.973	0.233	11	0.964
	ML shank Acc	0.968	0.254	11		0.966	0.262	11		0.974	0.226	10	
	ML thigh Acc	0.923	0.393	12		0.944	0.335	12		0.946	0.329	12	

- **Paired comparison similarity highest with these 2 signals** with control group (side-to-side indoor similarity) compared to intervention group (indoor-to-outdoor comparisons)



		SELF-SELECTED				SLOW				FAST			
	Signal	cosine		Euclidean		cosine		Euclidean		cosine		Euclidean	
		p	z	p	z	p	z	p	z	p	z	p	z
High	SI shank Acc	0.81	-0.23	0.86	0.06	1.00	-0.22	0.97	0.15	0.16	0.32	0.08	-0.43
	ML shank AV	0.76	-0.15	0.72	0.00	0.48	0.17	0.38	-0.15	0.12	0.23	0.11	-0.26
	SI thigh Acc	0.52	0.02	0.52	-0.05	0.47	-0.70	0.59	0.42	0.02	0.30	0.01	-0.49
	ML thigh AV	0.04	0.41	0.04	-0.48	0.10	0.34	0.08	-0.39	0.02	0.44	0.01	-0.62
	AP shank AV	<0.01	1.06	<0.01	-1.38	<0.01	1.30	<0.01	-1.58	<0.01	1.16	<0.01	-1.53
Middle	AP shank Acc	0.02	0.57	0.01	-0.72	0.01	0.58	0.01	-0.68	<0.01	0.65	<0.01	-0.87
	AP thigh Acc	0.72	-0.02	0.56	-0.15	0.40	0.19	0.23	-0.29	0.24	0.32	0.10	-0.53
	AP thigh AV	<0.01	10.28	<0.01	-16.78	<0.01	6.68	<0.01	-10.49	<0.01	6.21	<0.01	-9.57
	SI shank AV	<0.01	9.10	<0.01	-14.49	<0.01	11.06	<0.01	-17.44	<0.01	10.18	<0.01	-16.77
Low	SI thigh AV	<0.01	18.49	<0.01	-29.39	<0.01	10.90	<0.01	-16.67	<0.01	12.65	<0.01	-20.07
	ML shank Acc	<0.01	2.64	<0.01	-3.59	<0.01	2.93	<0.01	-4.01	<0.01	2.53	<0.01	-3.45
	ML thigh Acc	<0.01	8.30	<0.01	-12.22	<0.01	5.67	<0.01	-8.05	<0.01	6.23	<0.01	-9.01

Conclusions & Future Applications

Primary Study Findings

- Two specific raw gait signals with high similarity scores newly identified: Acceleration X (SI axis) shank & Angular Velocity Y (ML axis) shank

Secondary Study Findings

- Defined new control method for similarity testing
- New statistical comparison method for similarity testing

Applications

New identification of specific signals from wearable IMU's for deep learning model (enables moving from retrospective to real-time gait analysis):

1. **Help develop exoskeletons/prosthetics** (to assist gait disabilities, by programming soft muscle-like dielectric elastomer actuator "smart materials")
2. **Use gait for medical diagnosis** (in early assessment of neuromuscular disorders in all ages, inc elderly)

VALIDATION - Assess data model in pathologic gait

- Use this gait analysis technique (healthy patients) to assess data from neuromuscular disease patients
- Lab has cerebral palsy data for the study

TRANSLATION - AFO control module programming

- **Machine learning programming with gait detection** (develop programming for robotic prosthetics for patients with cerebral palsy)
- Train machine learning models using these 2 signals

All Images and Figures from Kahlon et al. 2023