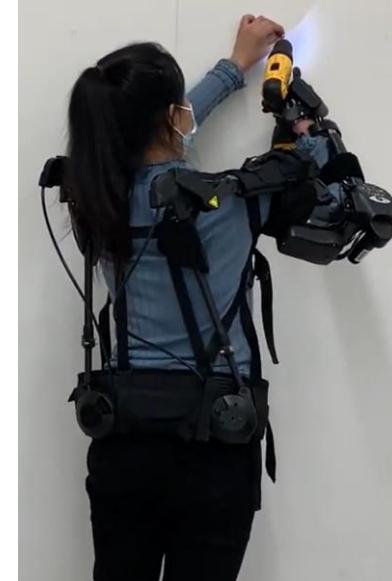
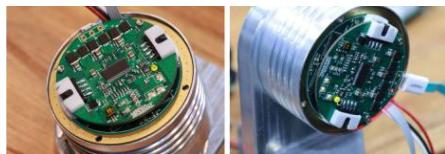
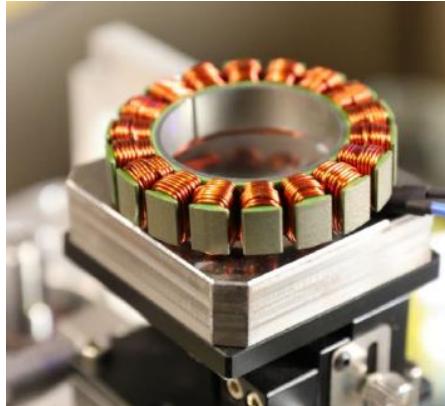


High-Performance Soft Robots for Human Augmentation

New Paradigm of Design and Control for Scientific Discovery

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**NC STATE
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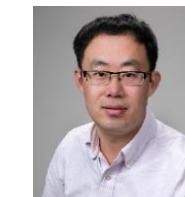
Israel Dominguez
(Ph.D. student)



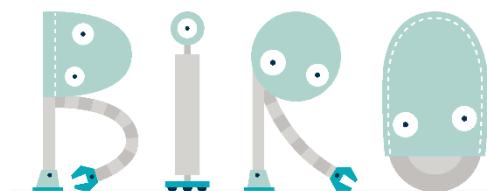
Sainan Zhang
(Ph.D. student)



Shuzhen Luo
(Postdoc)



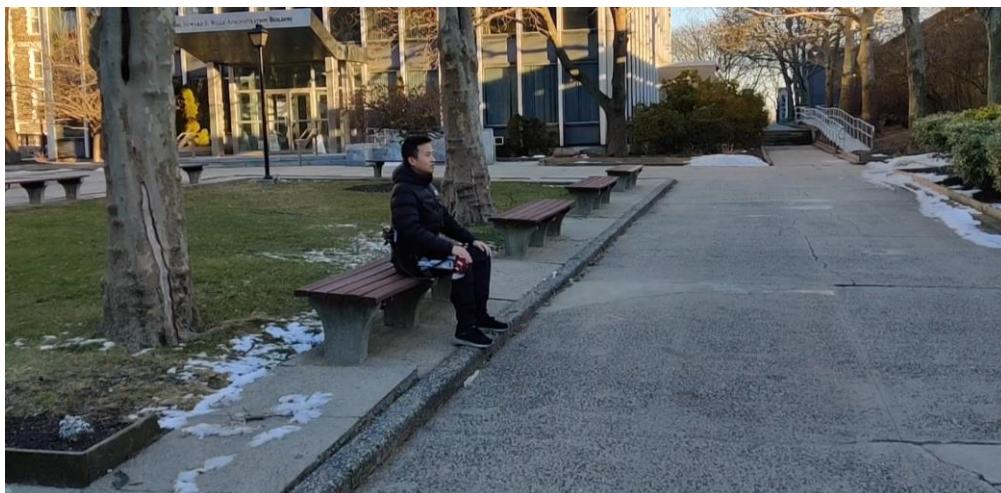
Hao Su
(PI)



BIOMECHATRONICS AND INTELLIGENT ROBOTICS

Exoskeleton Assists Walking Outdoors

- Lightweight knee exoskeleton: unilateral 2.1 kg, bilateral 3.5 kg
- Compliant and high control bandwidth



Modeling of Human-Robot Interaction

- ### – **Motor:** motor torque

$$L \frac{di}{dt} + RI + V = V_b \quad \tau_m = k_t i$$

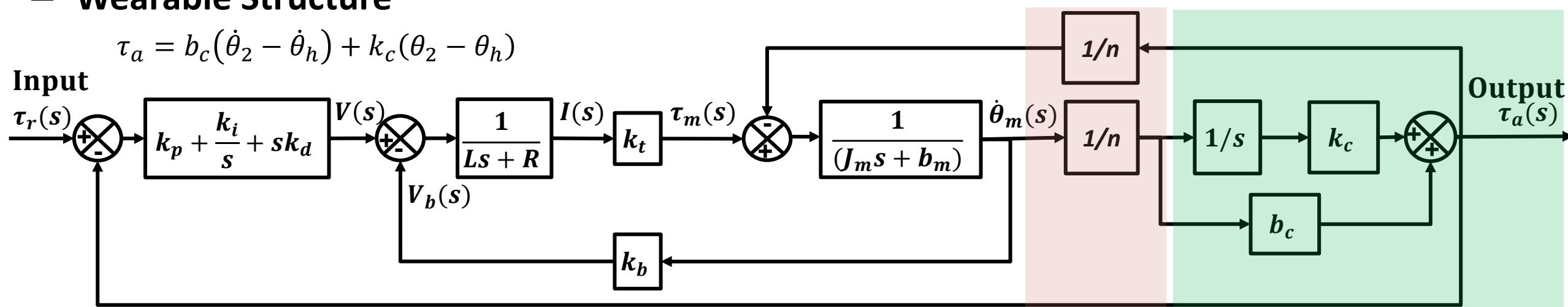
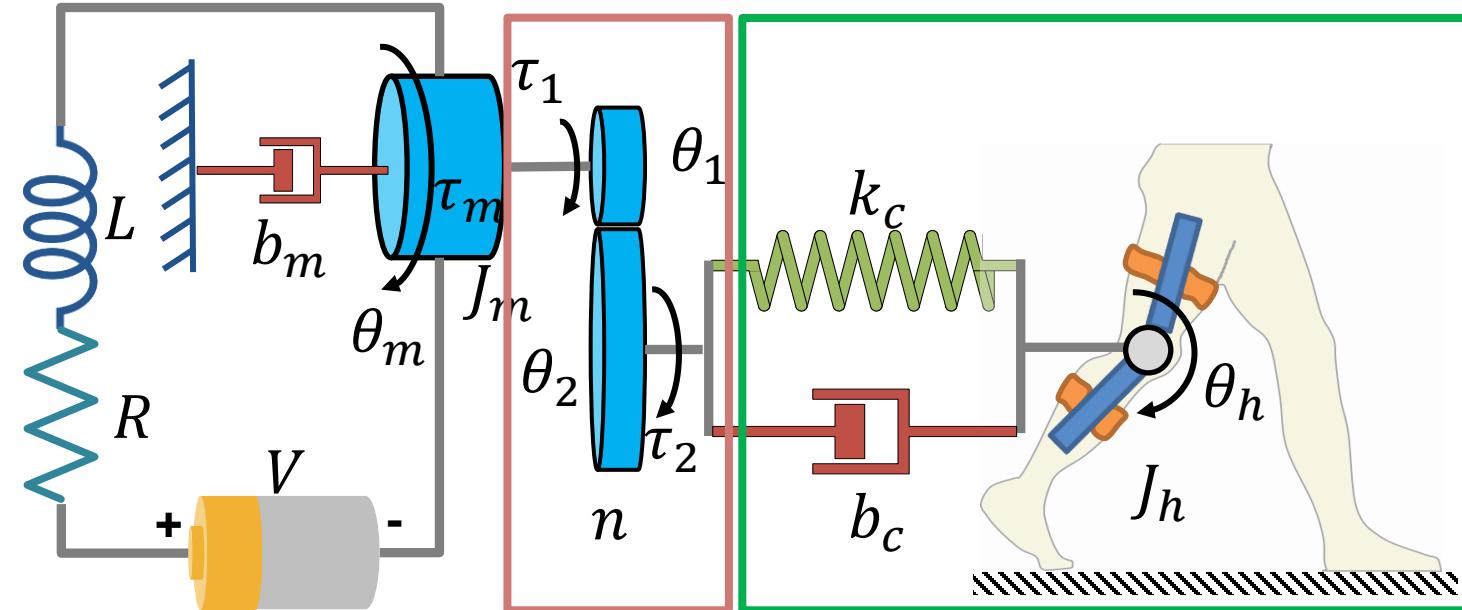
$$\tau_m = J_m \ddot{\theta}_m + b_m \dot{\theta}_m + \tau_1$$

- **Transmission:** torque amplification

$$\tau_2 = n\tau_1 \quad \theta_2 = \theta_1/n$$

- ## – Wearable Structure

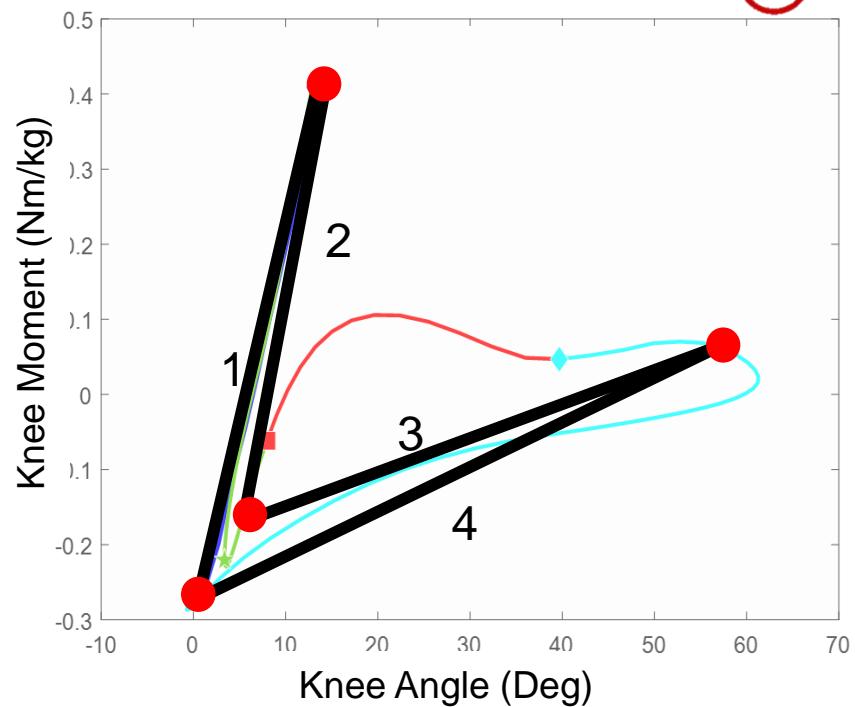
$$\tau_a = b_c(\dot{\theta}_2 - \dot{\theta}_h) + k_c(\theta_2 - \theta_h)$$



Stiffness Model Based Continuous Torque Control

State-of-the-Art [Zhang 17]

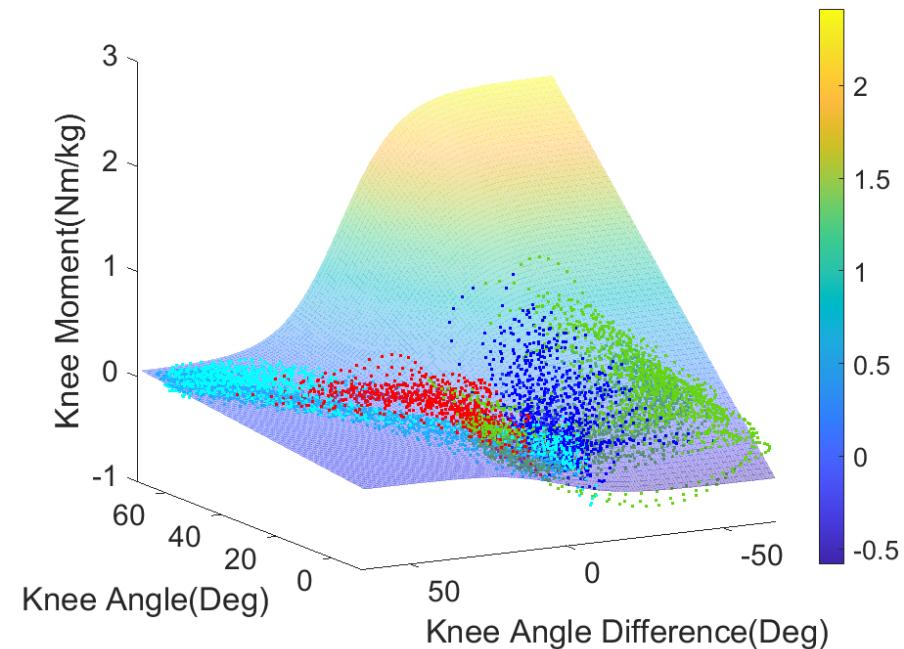
- Predefined piecewise torque
- Discrete stiffness



Smooth
→
Robust

Our Solution

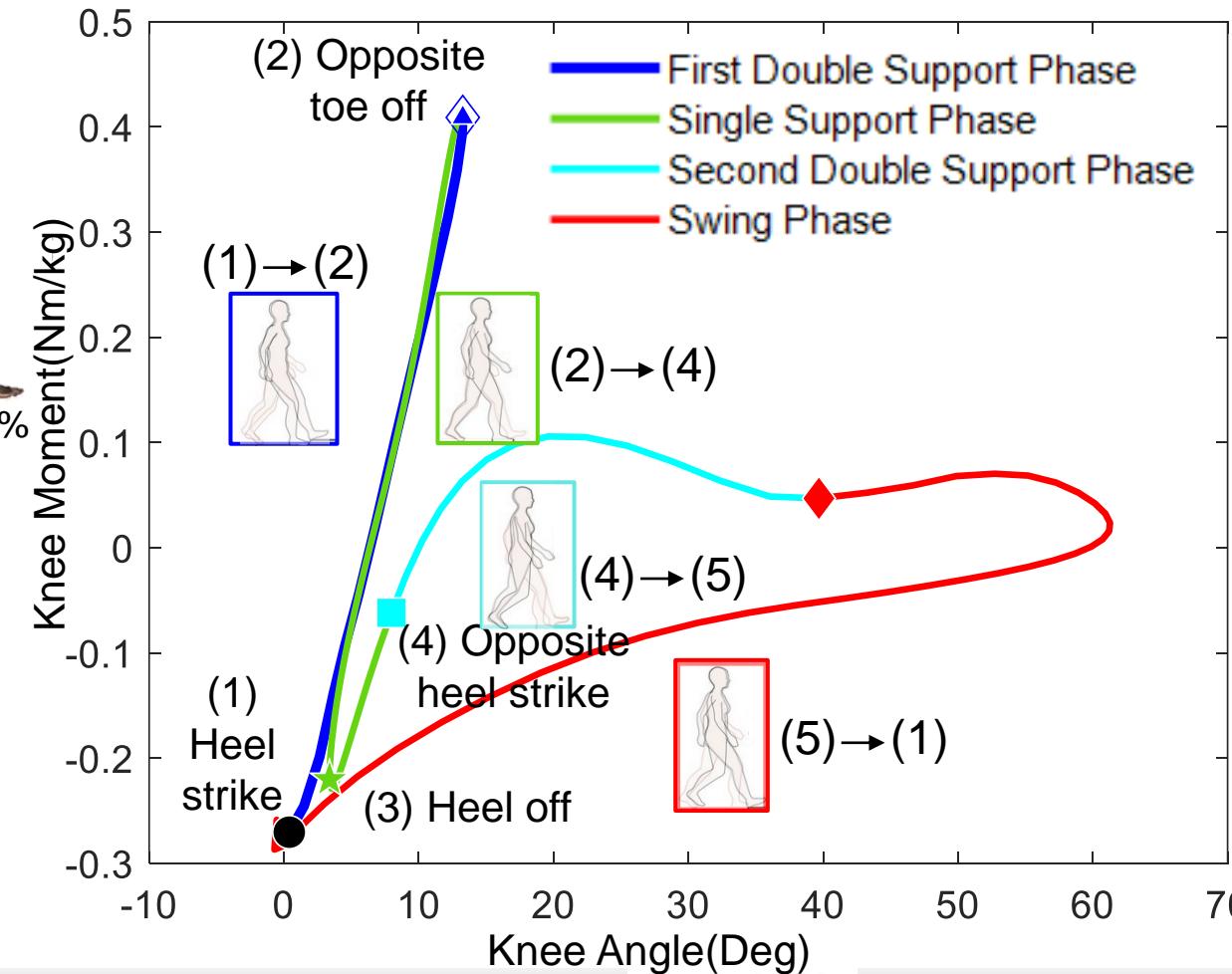
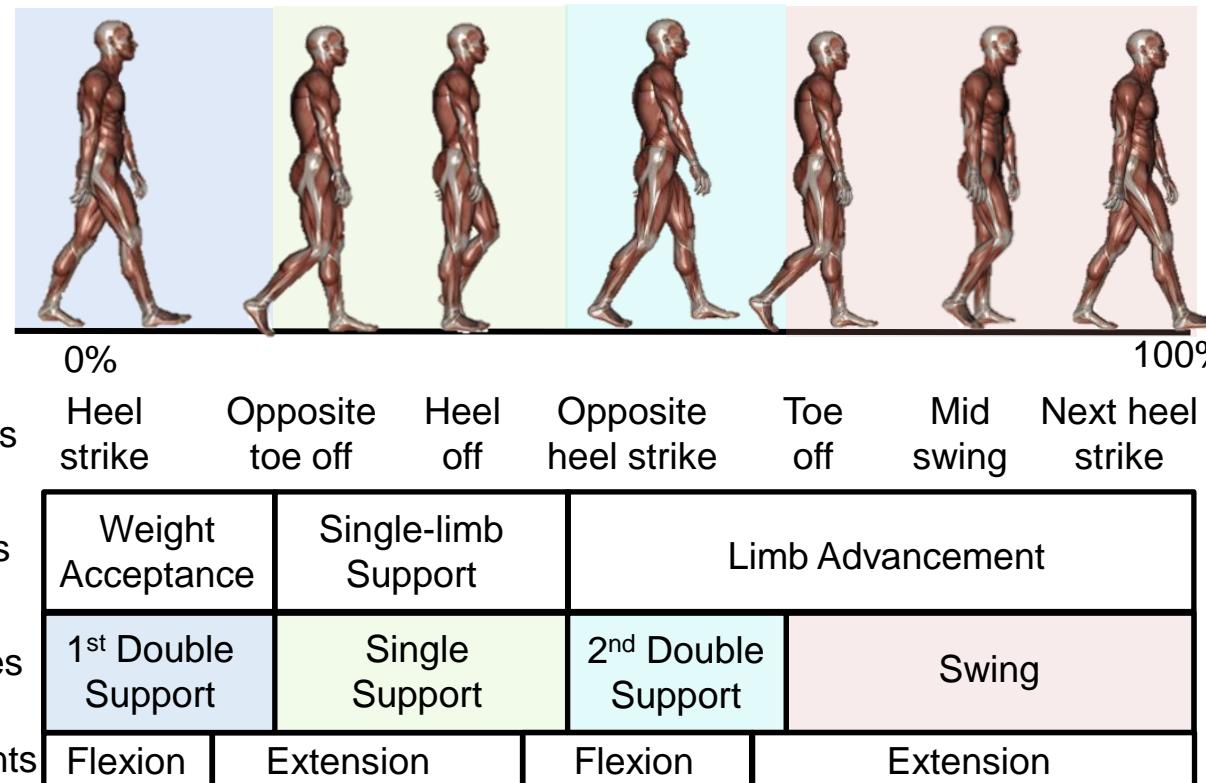
- Model based continuous torque
- Unique correspondence between torque and kinematics



- Zhang, J., & Collins, S. H. (2017). The passive series stiffness that optimizes torque tracking for a lower-limb exoskeleton in human walking. *Frontiers in neurorobotics*, 11, 68.
- Huang, T. H., Zhang, S., Yu, S., MacLean, M., Di Lallo, A., Bulea, C. T., Su, H., Modeling and Continuous Stiffness Torque Control of Quasi-Direct-Drive Knee Exoskeletons for Versatile Walking Assistance, *IEEE Transaction on Robotics*, 2021 (accepted)

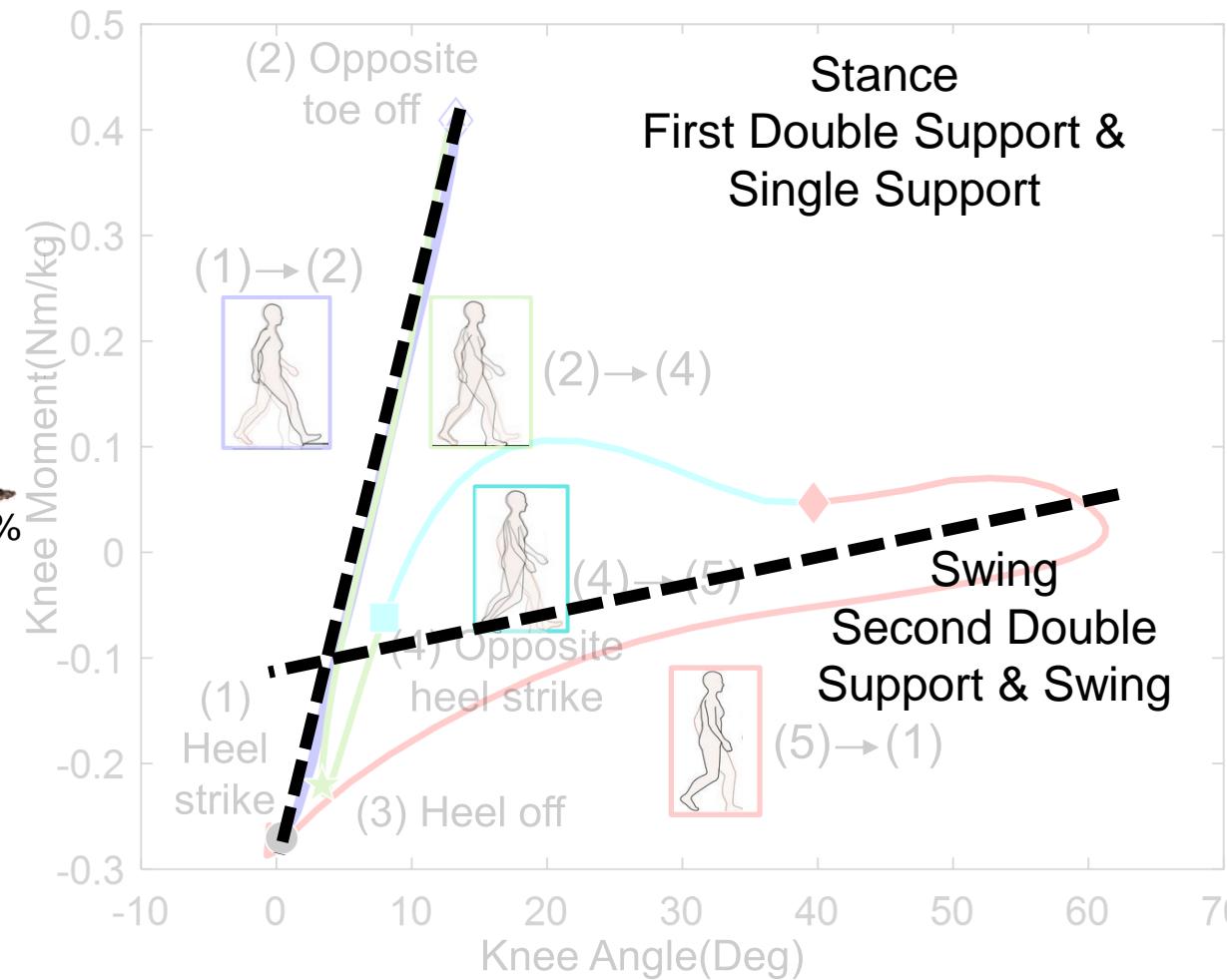
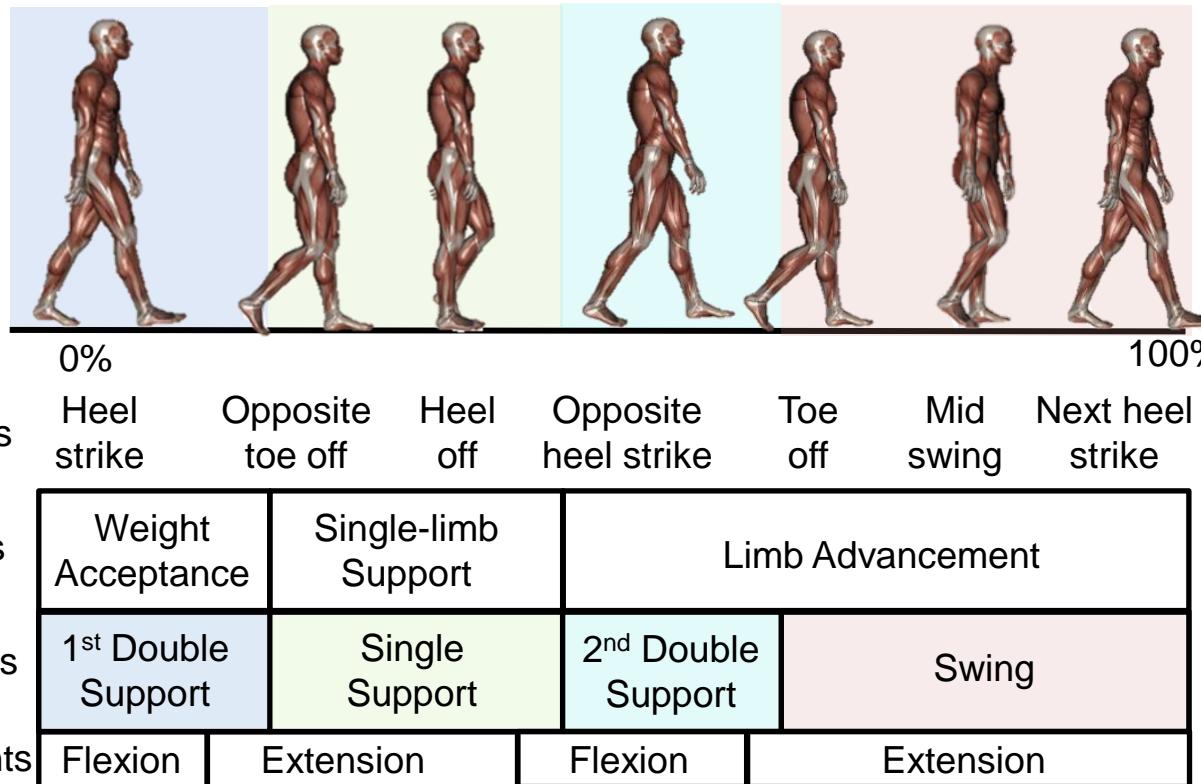
Biomechanics-inspired Continuous Torque Estimation

Can we identify methods for simple and adaptive torque control to sync with human?



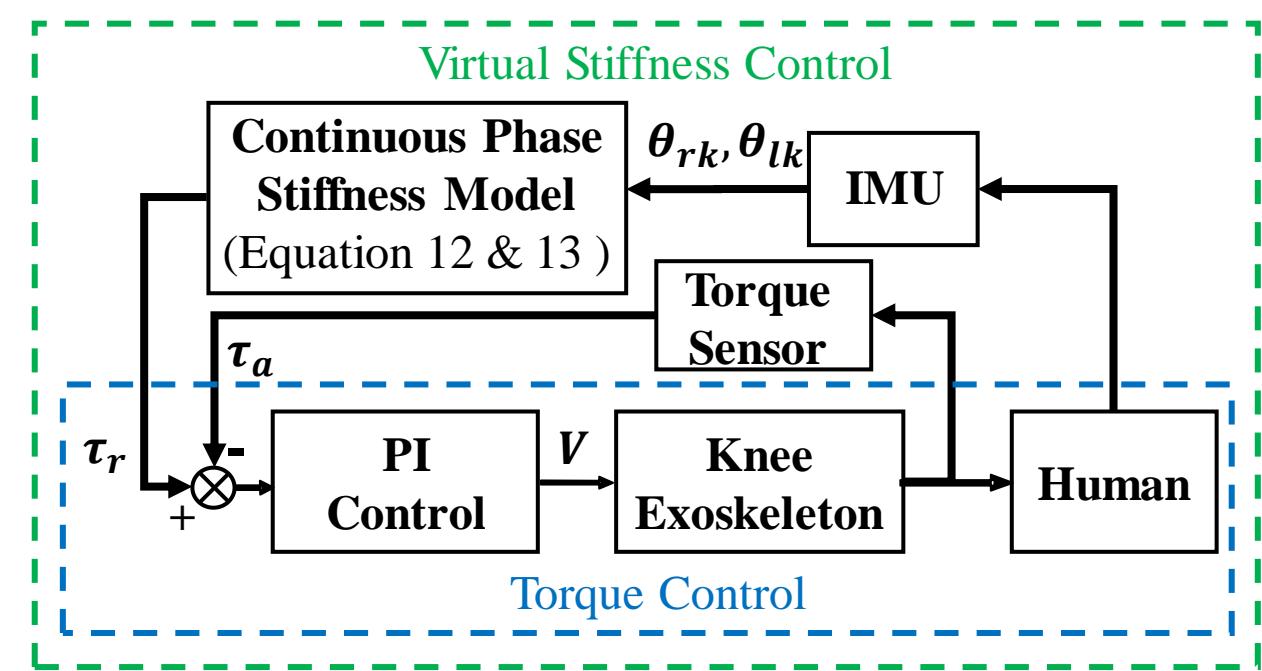
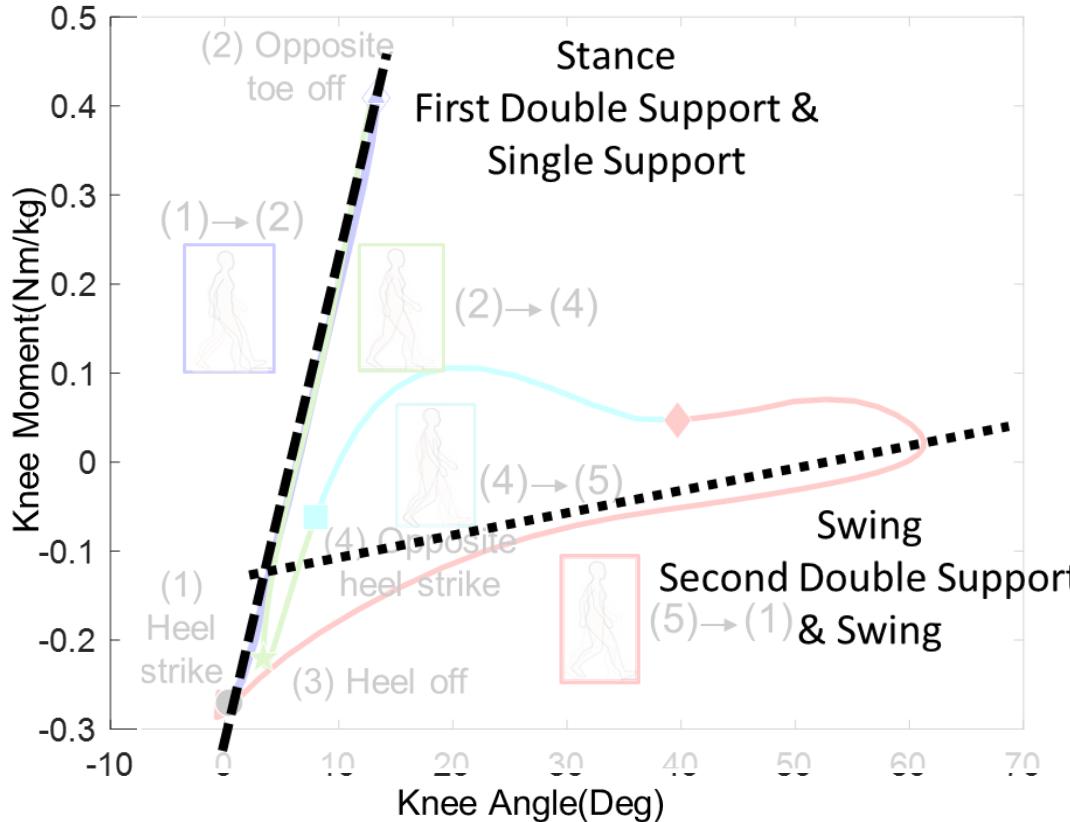
Biomechanics-inspired Continuous Torque Estimation

- Stance phase: high stiffness
- Swing phase: low stiffness



Stiffness Model Based Continuous Torque Estimation

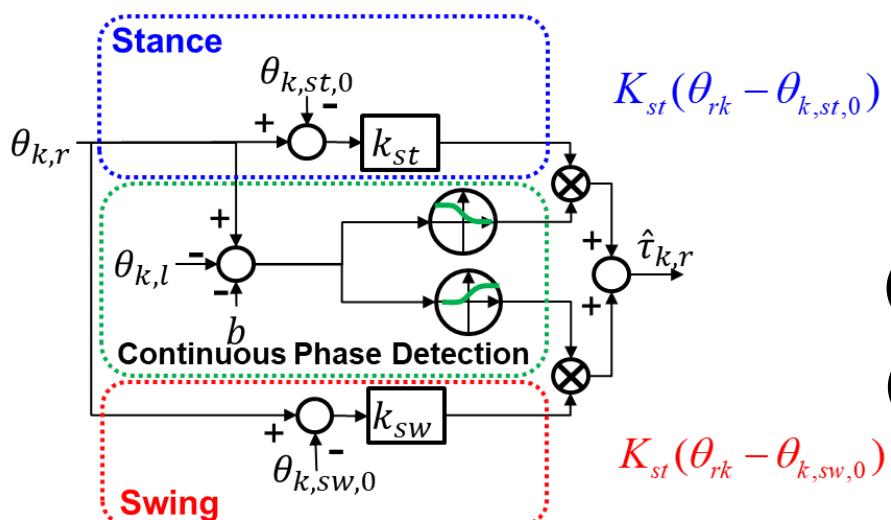
- Stance: 1st Double Support Phase + Single Support Phase
- Swing: 2nd Double Support Phase + Swing



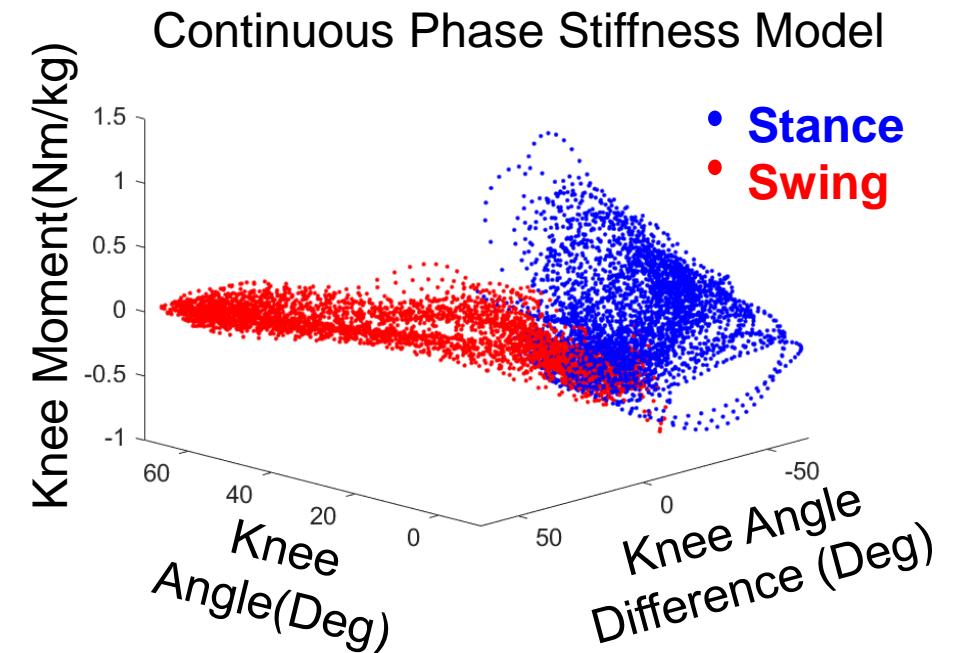
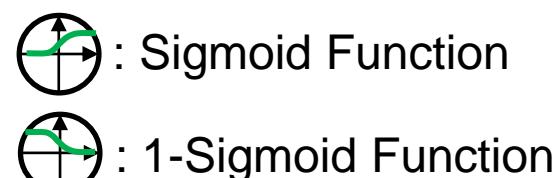
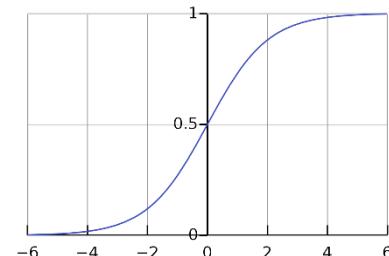
Stiffness Model based Continuous Torque Estimation

- **Input:** knee angles $\theta_{k,r}, \theta_{k,l}$ and their difference; **Output:** estimated knee torque
 - Knee moment estimation by linear combination of stance and swing
- $$\hat{\tau}_{k,r} = [1 - S(\theta_{k,r}, \theta_{k,l})]k_{st}(\theta_{k,r} - \theta_{k,st,0}) + S(\theta_{k,r}, \theta_{k,l})k_{sw}(\theta_{k,r} - \theta_{k,sw,0})$$

- Sigmoid function: discrete to continuous



$$S(\theta_{k,r}, \theta_{k,l}) = \frac{1}{1 + e^{-af(\theta_{k,r}, \theta_{k,l})}} \quad f(\theta_{k,r}, \theta_{k,l}) = (\theta_{k,r} - \theta_{k,l}) - b$$



Stiffness Model based Continuous Torque Estimation

- Knee torque estimation: linear combination of stance and swing stiffness models

$$\hat{\tau}_{k,r} = [1 - S(\theta_{k,r}, \theta_{k,l})]k_{st}(\theta_{k,r} - \theta_{k,st,0}) + S(\theta_{k,r}, \theta_{k,l})k_{sw}(\theta_{k,r} - \theta_{k,sw,0})$$

$$S(\theta_{k,r}, \theta_{k,l}) = \frac{1}{1 + e^{-af(\theta_{k,r}, \theta_{k,l})}} \quad f(\theta_{k,r}, \theta_{k,l}) = (\theta_{k,r} - \theta_{k,l}) - b$$

- Nonlinear optimization to identify optimal hyperplane separating gait phases

- Objectives function

$$\arg \min \sum_{i=1}^m (\hat{\tau}_{k,r,i} - \tau_{k,r,i})^2$$

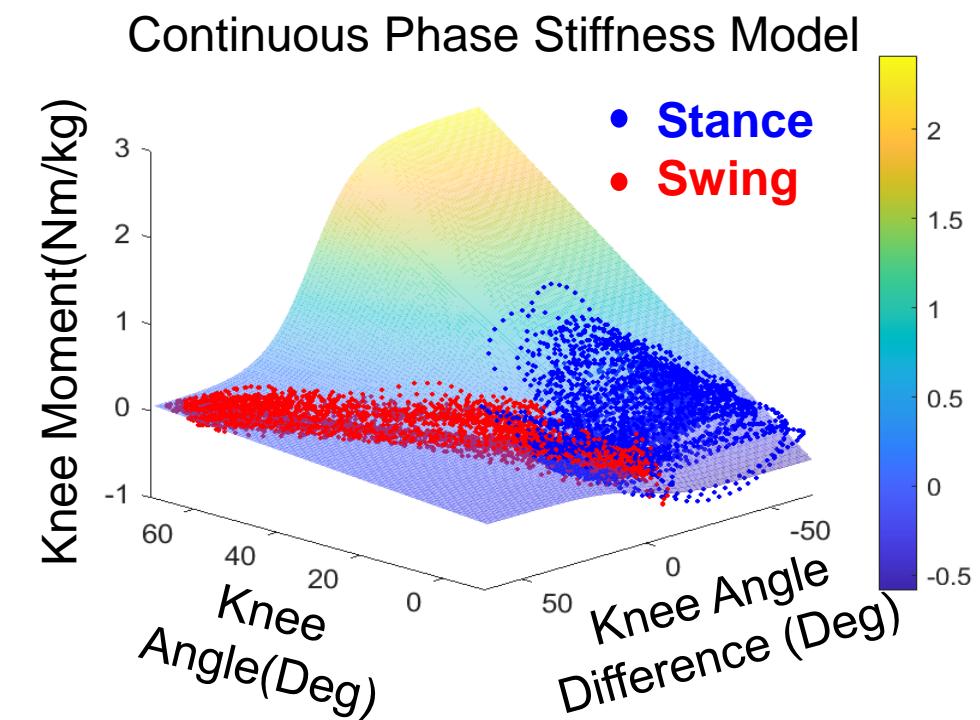
- Optimization Parameters

$$W = [k_{st}, k_{sw}, \theta_{k,st,0}, \theta_{k,sw,0}, a, b]$$

k_{st} & k_{sw} : stance and swing stiffness

$\theta_{k,st,0}$ & $\theta_{k,sw,0}$: the initial angle for two stiffness models

a & b: transition area width and center

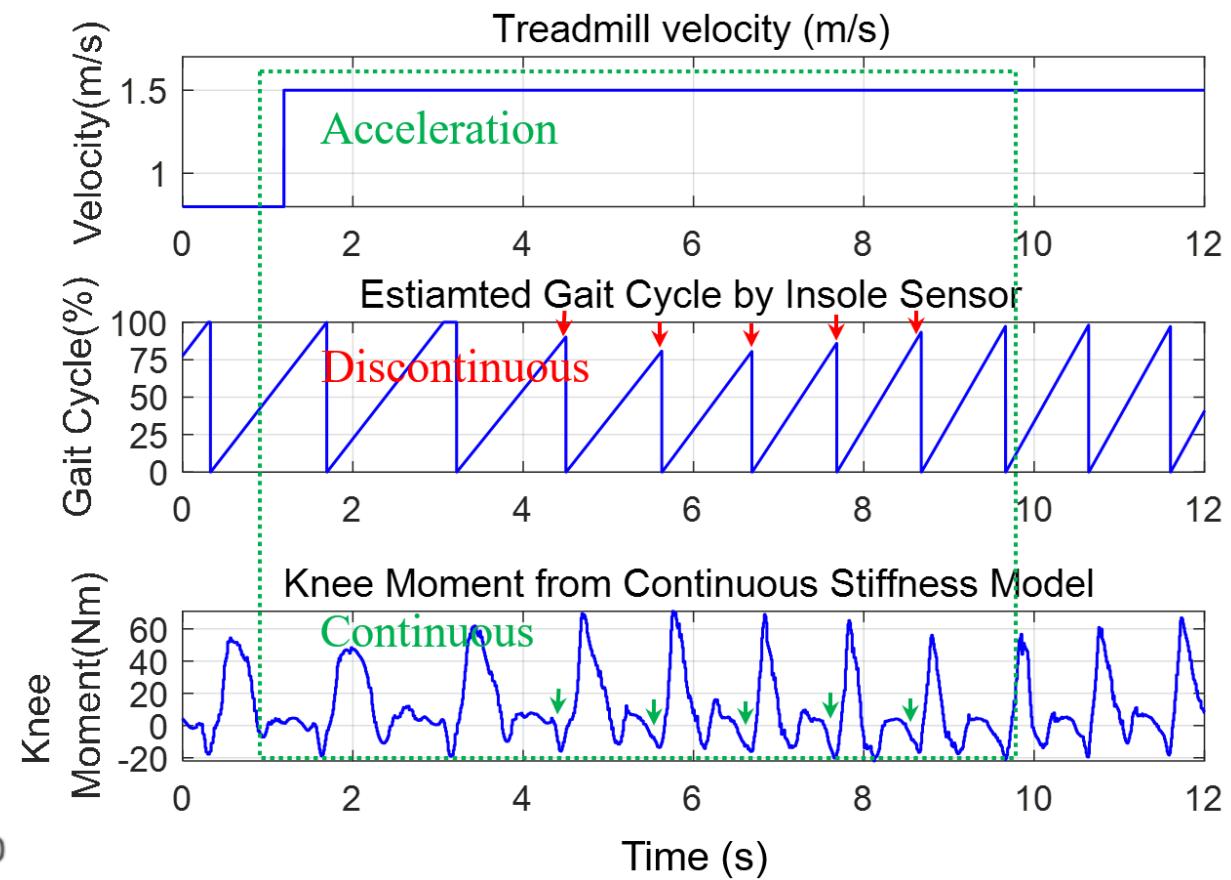
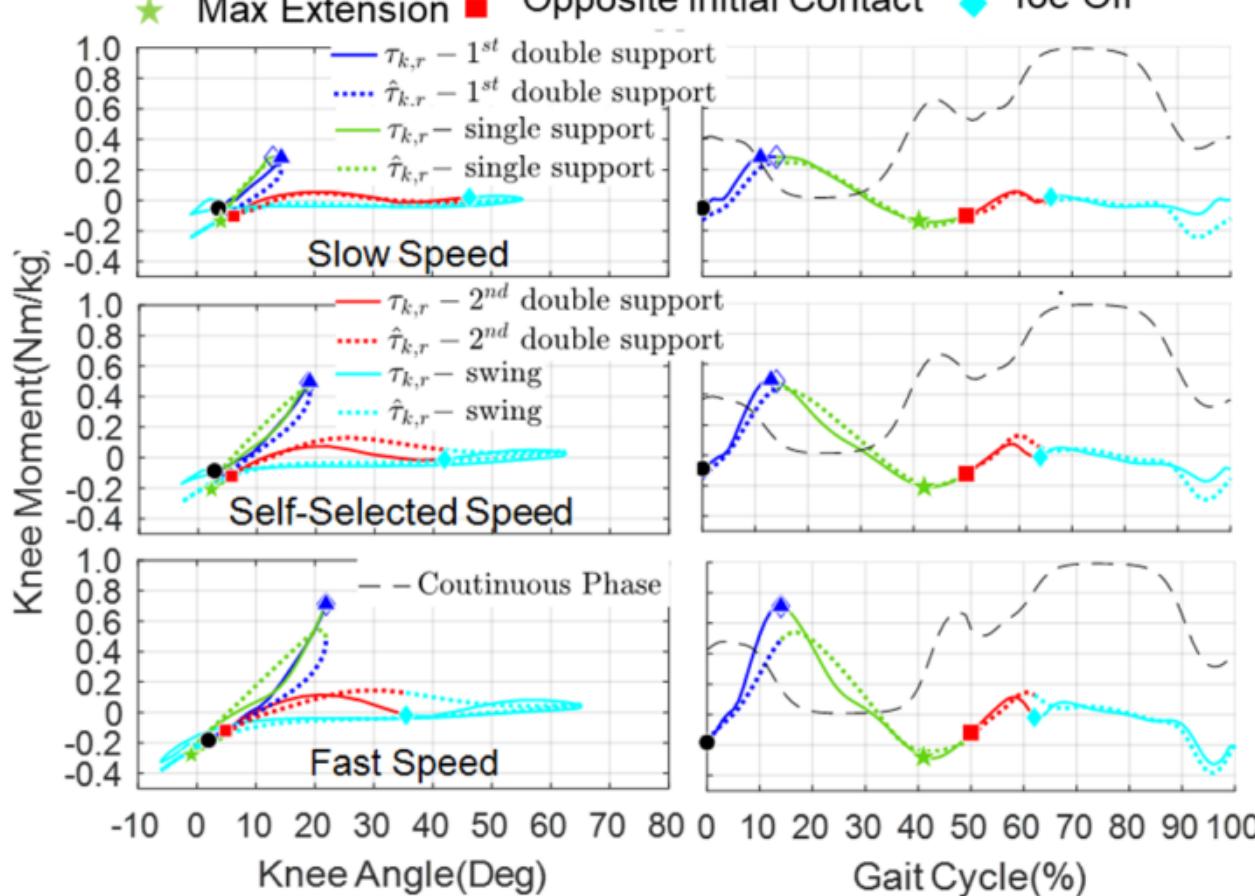


Torque Estimation for Gait Synchronization Control

- Estimated torque continuously adapts to biological torque at varying speeds

- Initial contact Opposite Toe Off Max Flexion

- Max Extension Opposite Initial Contact Toe Off



Human Subject Experiment

- 8 able-bodied subjects: 6 males and 2 females

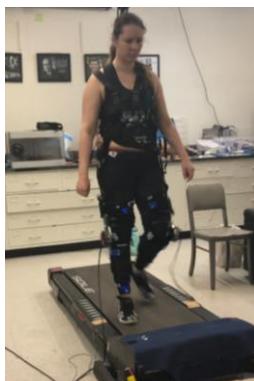
1 st visit (Habituation)						
Powered 1	Rest	Unpowered 1	Rest	Powered 2	Rest	Unpowered 2
20 mins	10 mins	20 mins	10 mins	20 mins	10 mins	20 mins

Randomized

2nd visit (Evaluation)

Baseline		Rest 10 mins	Powered		Rest 10 mins	Unpowered	
Adaption	Collect Data		Adaption	Collect Data		Adaption	Collect Data
5 min	60 strides		5 min	60 strides		5 min	60 strides

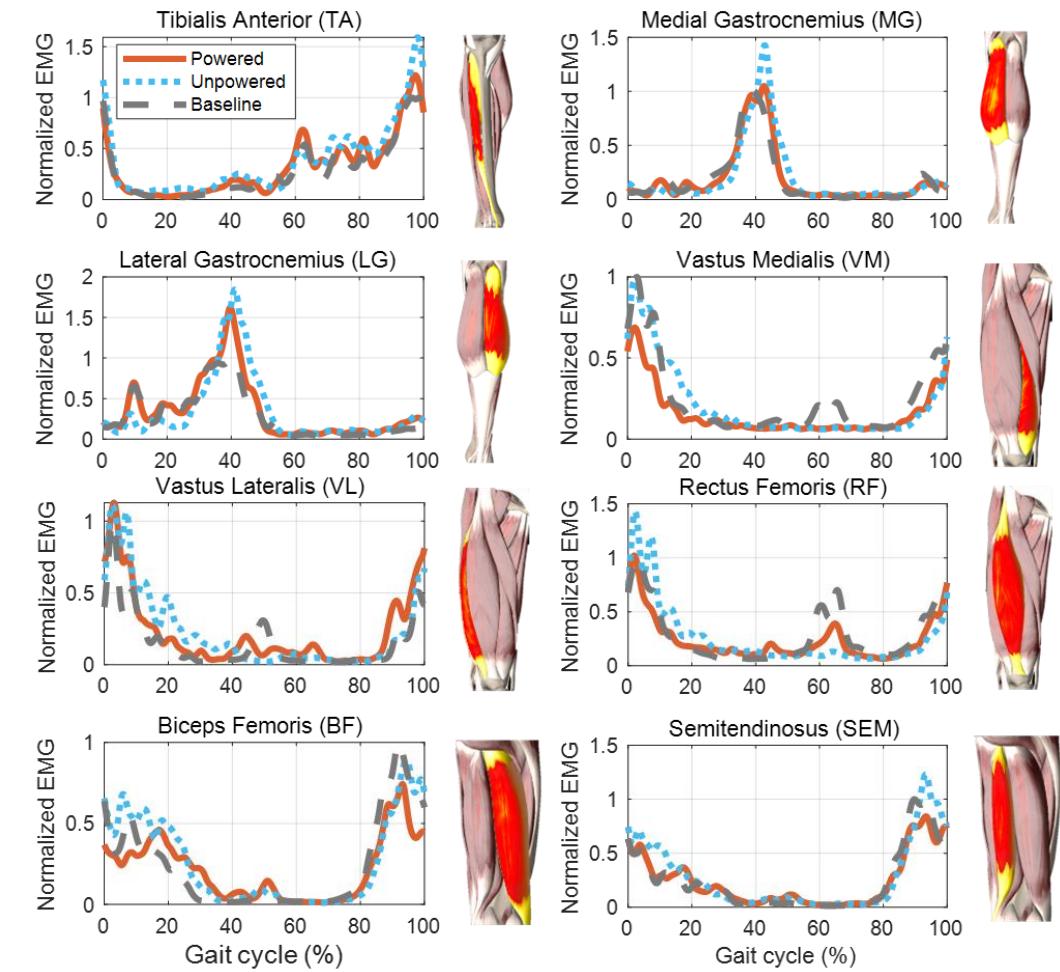
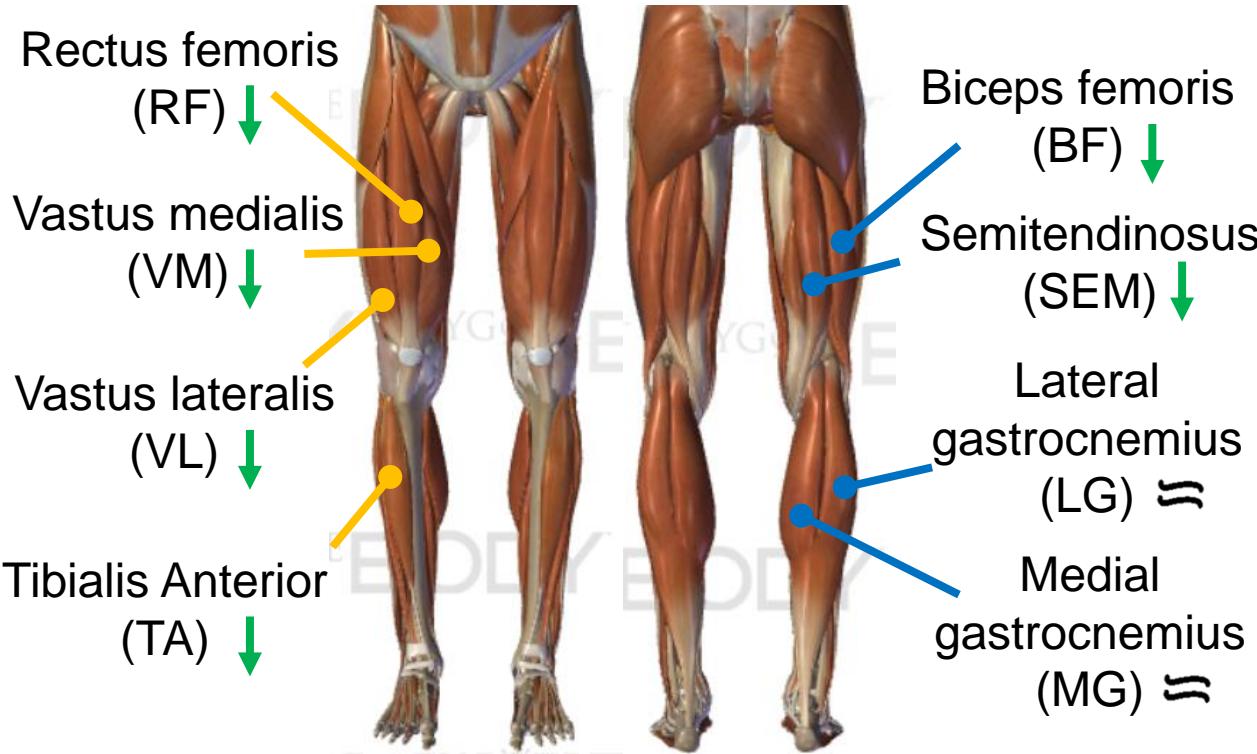
Randomized



Demo videos

First Work to Show EMG Reduction with Portable Knee Exo

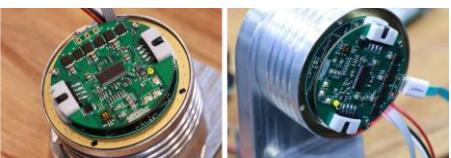
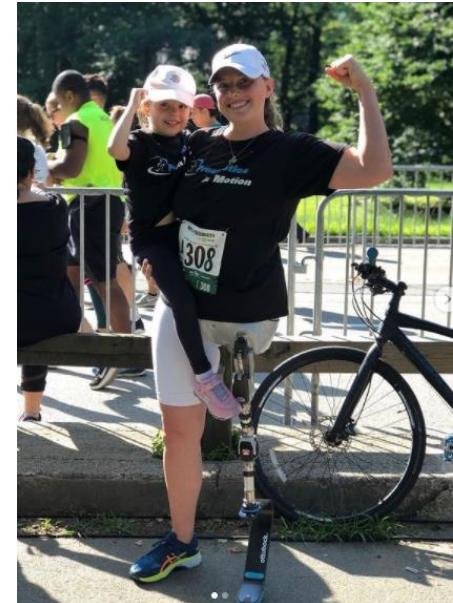
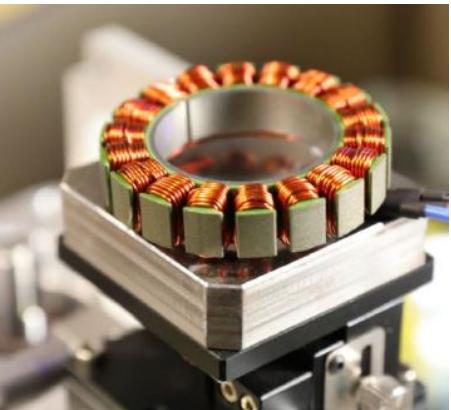
- Reduced 3.7 - 15.7% muscle activation for knee **extensors** and **flexors**, and ankle **extensors**



Reinforcement Learning and Control of a Lower Extremity Exoskeleton

Israel Dominguez, Menghan (Meghan) Jiang, Shuzhen (Susan) Luo, and Hao Su^{1*}

¹Lab of Biomechatronics and Intelligent Robotics, Mechanical and Aerospace Engineering, North Carolina State University (NCSU)



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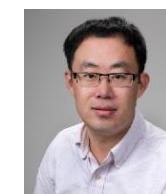
Israel Dominguez
(Ph.D. student)



Shuzhen Luo
(Postdoc)



Menghan Jiang
(PhD Student)



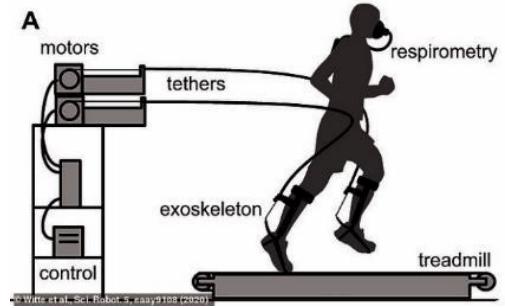
Hao Su
(PI)



BIOMECHATRONICS AND INTELLIGENT ROBOTICS

Paradigm Shift from Lab to Community Use

Tethered Exoskeleton



Portable Exoskeleton



2012 Ekso Bionics
Increased metabolic cost

- **12.5-30 Kg**
- **High friction**
- **Resistive**

Rigid Exoskeletons

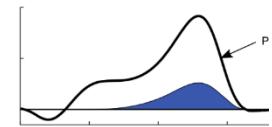
Low torque motors



High ratio transmission



Discrete Controller



Challenges

Low torque, high speed

Innovations

High torque motor



Quasi-direct Drive



Resistive to natural movements



Steady-state walking only

Versatile Continuous

Our Exoskeleton

- **Lightweight: 1.7 Kg (unilateral)**
- **Compliant**
- **Versatile**

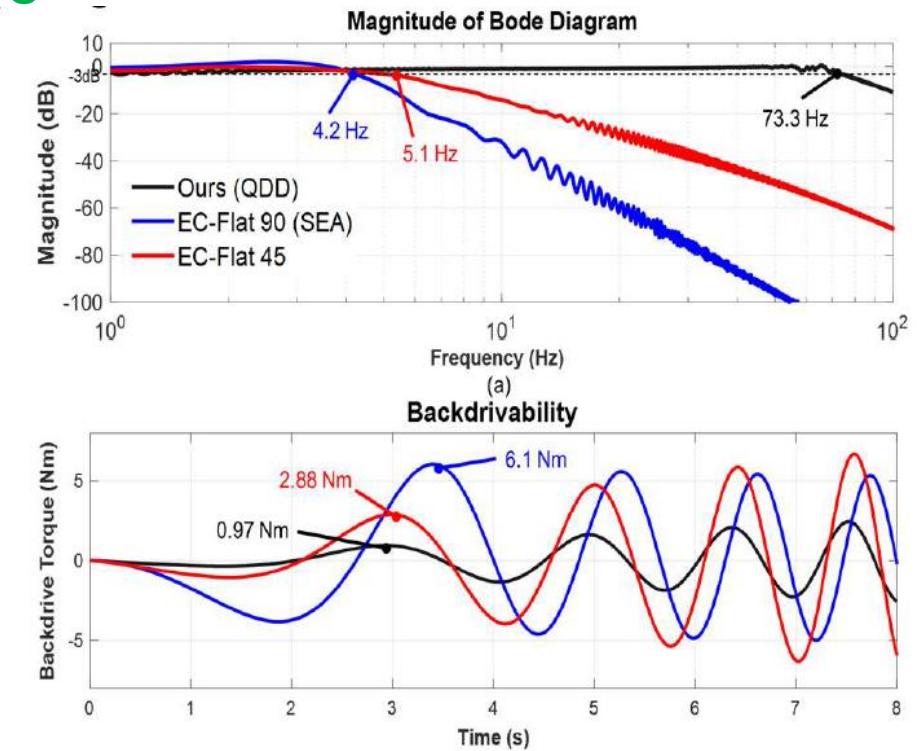


- Yu, Huang, Yang, Jiao, Yang, Chen, Yi, Su. Quasi-direct drive actuation for a lightweight hip exoskeleton with high backdrivability and high bandwidth. **IEEE Transactions on Mechatronics**, 2020 (**Best student paper award**)
- Huang, Zhang, Yu, MacLean, Zhu, Di Lallo, Jiao, Bulea, Zheng, & Su, Modeling and Stiffness-based Continuous Torque Control of Lightweight Quasi-Direct-Drive Knee Exoskeletons for Versatile Walking Assistance, **IEEE Transactions on Robotics**, 2022

Paradigm Shift from Lab to Community Use

- Our actuators have **low backdrive torque and high bandwidth**

	Backdrive Torque	Torque Control Bandwidth
Conventional	2.9 Nm (Middle)	5.1 Hz (Low)
SEA	6.1 Nm (High)	4.2 Hz (Low)
Ours	1.0 Nm (Low)	73.3 Hz (High)



- Yu, Huang, Yang, Jiao, Yang, Chen, Yi, Su. Quasi-direct drive actuation for a lightweight hip exoskeleton with high backdrivability and high bandwidth. **IEEE Transactions on Mechatronics**, 2020. (**Best student paper award of ASME Mechatronics TC**)
- Huang, Zhang, Yu, MacLean, Zhu, Di Lallo, Jiao, Bulea, Zheng, & Su, Modeling and Stiffness-based Continuous Torque Control of Lightweight Quasi-Direct-Drive Knee Exoskeletons for Versatile Walking Assistance, **IEEE Transactions on Robotics**, 2022
- J. Zhu, C. Jiao, I. Dominguez, S. Yu, H. Su, "Design and Backdrivability Modeling of a Portable High Torque Robotic Knee Prosthesis With Intrinsic Compliance For Agile Activities", **IEEE/ASME Transactions on Mechatronics**, 2022

Challenge in State-of-the-Art

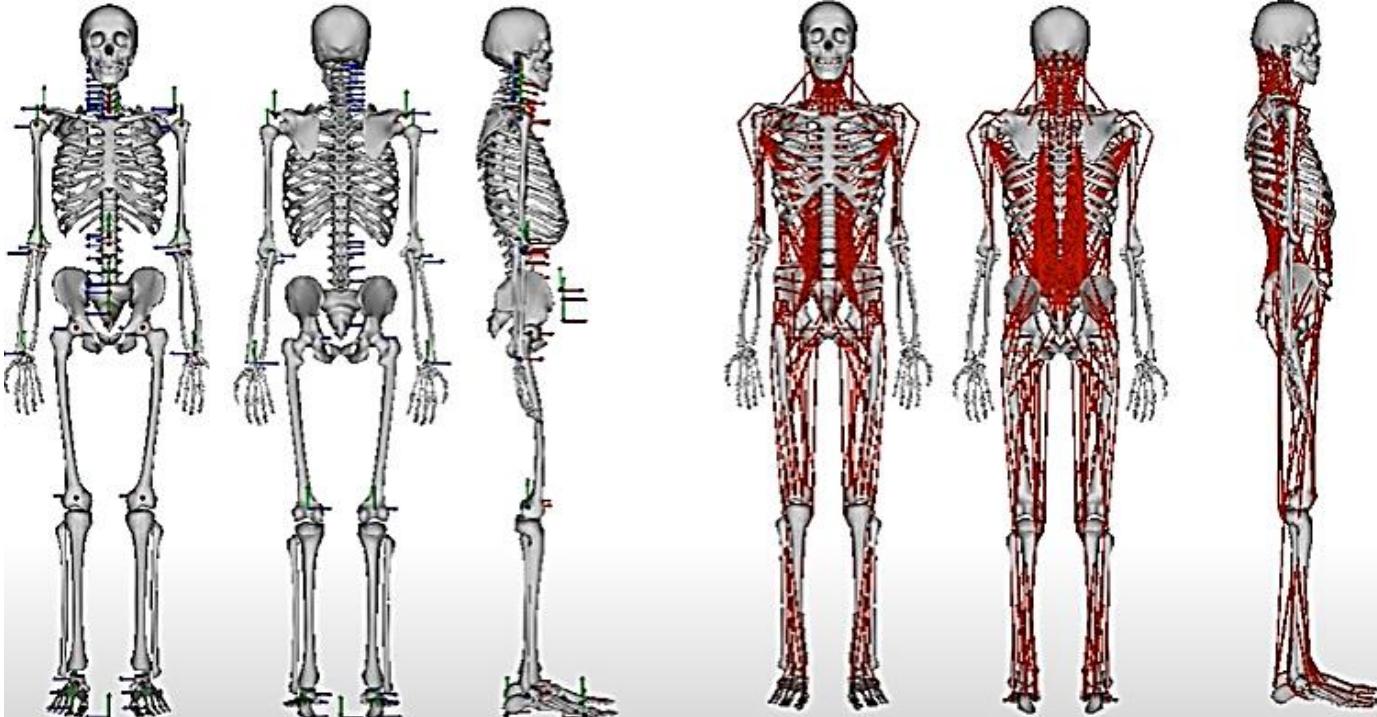
Challenge 1: intensive human testing, time-consuming, laborious



<https://exoedu.lu/materials/recorded-webinar-usage-of-medical-exoskeletons-04-11-20/>

Solution 1: High-Fidelity Simulation

- Human musculoskeletal Models: 50 DoFs whole-body models with 284 muscles



- Dynamics of musculoskeletal system:
$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{c}(\mathbf{q}, \dot{\mathbf{q}}) = \mathbf{J}_m^T \mathbf{f}_m(\mathbf{a}) + \mathbf{J}_{ext}^T \mathbf{f}_{ext}$$
- Forward ($\ddot{\mathbf{q}}$), and hybrid dynamics
- Many joint types:
 - Fixed, translational, rotational,
 - Spherical/ball, multi-DOF functional joint, etc.
- Muscle force types (Hill type muscle tendon unit)
$$\mathbf{F} = [\mathbf{a} \cdot F_L(l) \cdot F_V(\dot{l}) + F_P(l)] \times F_{max}$$

Challenge in State-of-the-Art

Challenge 2: Lack robustness to subject-specific conditions, require rigorous heuristic handcrafting of control parameters

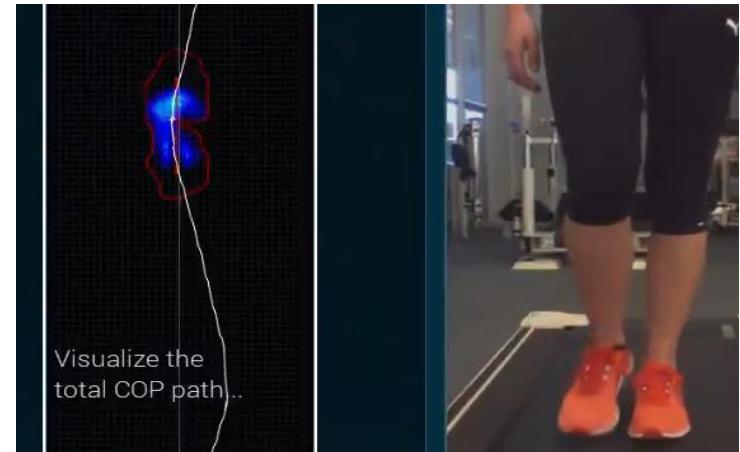


<https://med.uth.edu/blog/2019/08/29/international-symposium-on-wearable-robotics-coming-oct-16-18/>

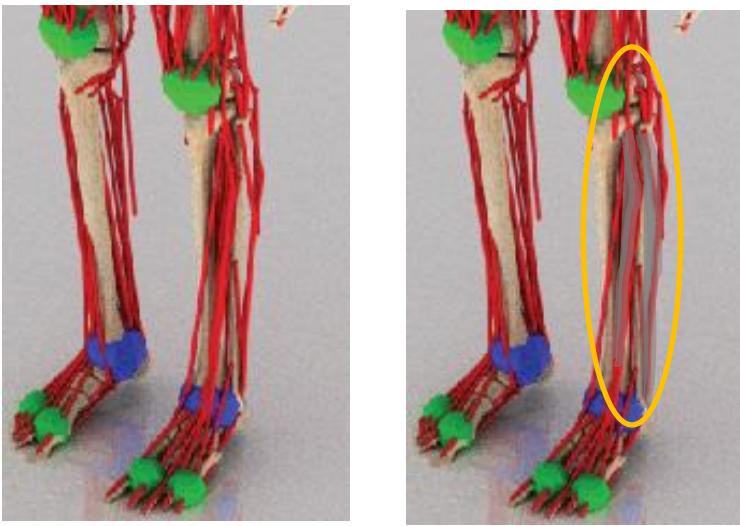
Solution 2: Dynamics Randomization of Muscle Strength Improves Robustness

- A Generalized controller that adapts to human variabilities
- Dynamics Randomization Machine Learning Method: randomizing muscle strength during control policy training facilitates robustness towards varying, or hemiplegic human conditions such as passive muscles (quadriplegic), muscle weakness
- Balance reward: The movement of system CoP highly correlates with stability and balance. Thus, reward is to motivate the current CoP position to stay inside a stable region around the center of the foot support
 - Reward $r_t = w^m r_m + w^p r_p + w^{root} r_{root} + w^{cop} r_{cop} + w^\tau r_\tau$

• Shuzhen Luo, Androwis Ghaith, Adamovich Sergei, Erick Nunez, Hao Su, and Xianlian Zhou. "Robust Walking Control of a Lower Limb Rehabilitation Exoskeleton Coupled with a Musculoskeletal Model via Deep Reinforcement Learning." (under review)



Normal Muscles Weakened Muscles

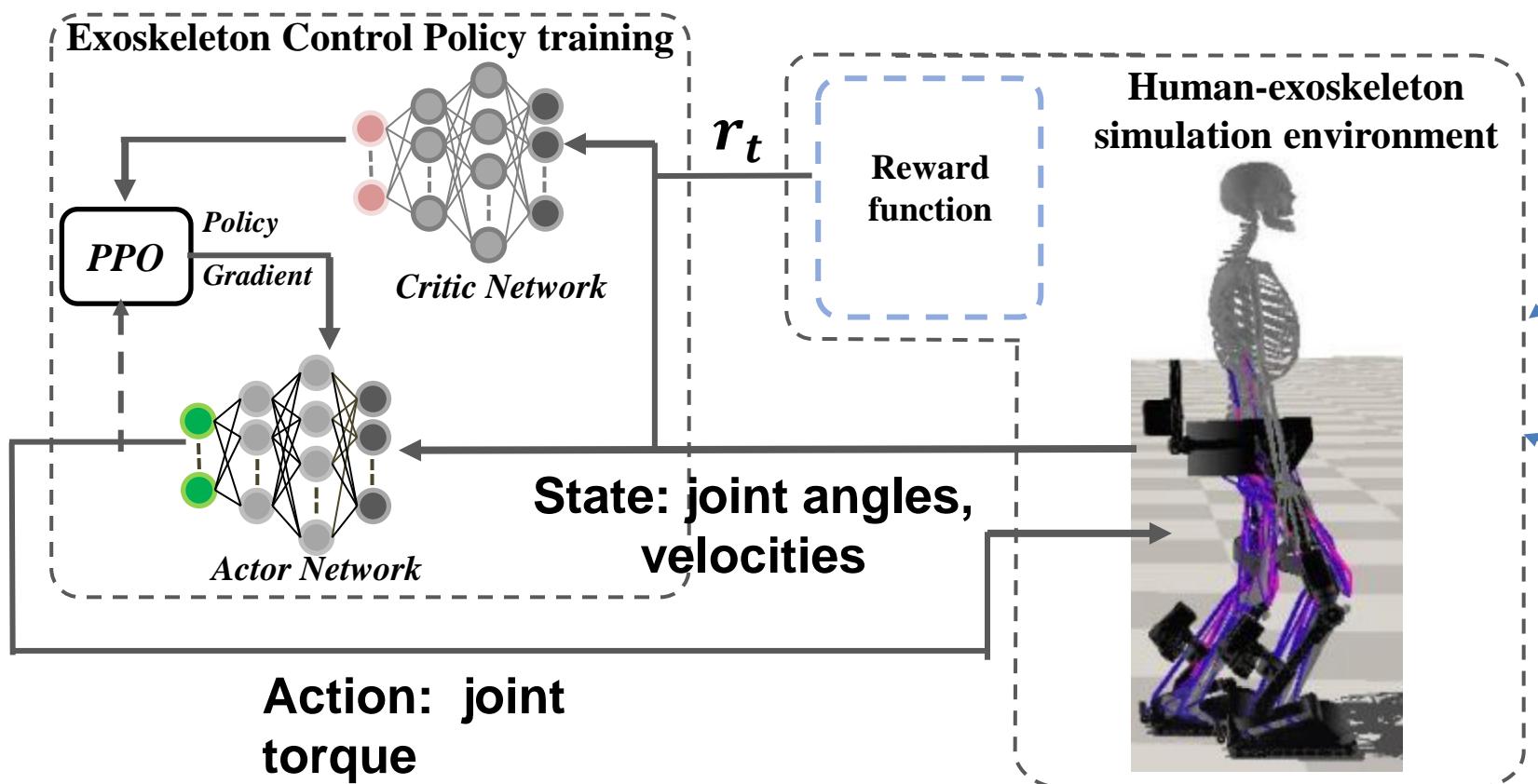


The Complete Picture

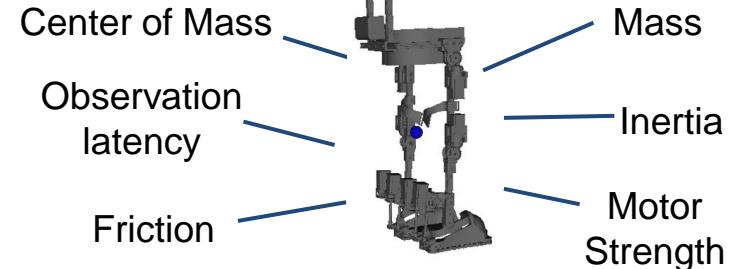
- Reinforcement Learning paradigm together with simulation environment developed a torque control policy for walking assistance
 - Our Trained Control Policy is:
 1. Alleviates need for human intensive testing
 2. Robust to human-exoskeleton interaction forces
 3. Independent of subject-specific conditions
 4. Not subject to myriad control parameter tuning
-
- The diagram illustrates the Reinforcement Learning (RL) and Control architecture for a lower extremity exoskeleton. It consists of three main components: a Human-Exo interaction environment, a Reinforcement Learning (RL) algorithm, and a neural network-based controller.
- Human-Exo interaction environment:** This component contains a 3D rendering of a human skeleton wearing an exoskeleton. It provides joint torque values ($\tau_1, \tau_2, \dots, \tau_8$) to the controller and sends a Reward signal back to the RL algorithm.
 - RL algorithm:** This component receives the Reward from the environment and provides a target joint angle action to the controller.
 - Controller:** The controller takes the target joint angle and various historical and current state information as input to produce joint torque commands.
 - Input History:** Joint state history, joint angle history, and joint angle velocity history are stored in a buffer.
 - Input Features:** The controller processes these histories along with current joint state history, previous action history, and future target motions to generate an Action: target joint angle.
 - Control Flow:** The target joint angle is processed through a Low pass filter, Preprocess action, and PD control blocks to produce the final Joint torque output.

Accelerate Sim-to-Real Transfer

- Gap between simulation environment and real world **degrades the performance** of policies when transferred to robots
- We randomized various parameters to inject dynamic uncertainties during the training process.
- This **expedites** Sim-To-Real transfer of trained policy and **improves** robustness of control



Robot dynamics randomization:

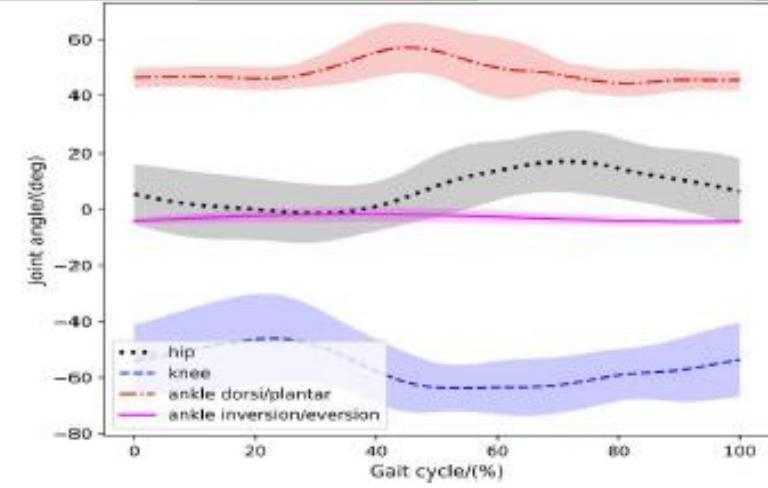
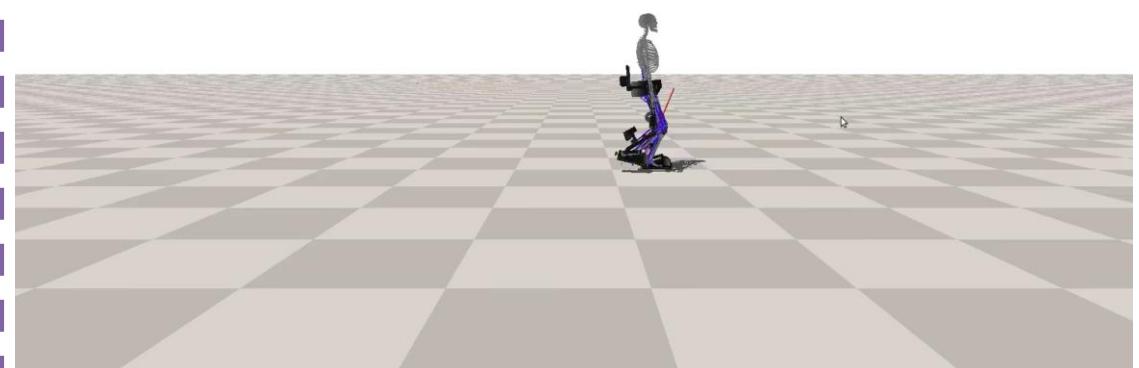
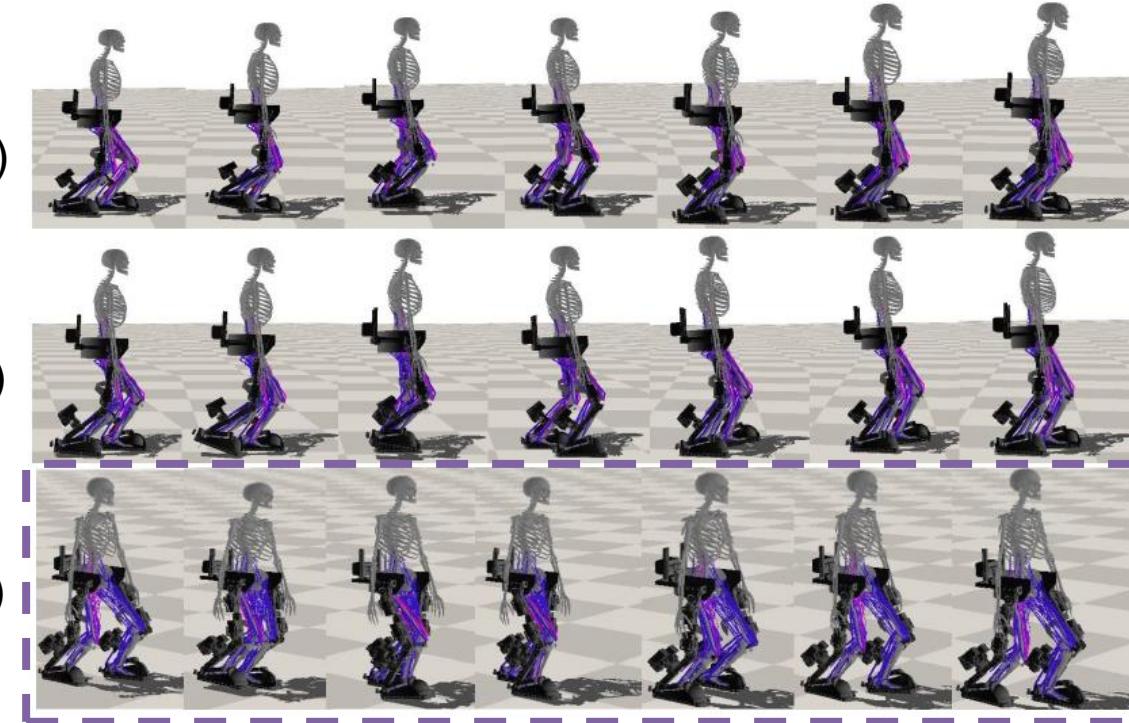


Dynamic Parameters	Training Range	Testing Range
Friction coefficient	[0.9,1.6]*default value	[0.7,2.0]*default value
Mass	[0.8,1.2]*default value	[0.7,1.5]*default value
Motor strength	[0.8,1.2]*default value	[0.7,1.3]*default value
Observation latency	[0,0.04]s	[0,0.06]s
Inertial	[0.5,1.5]*default value	[0.4,1.6]*default value
Center of Mass	[0.9,1.2]*default value	[0.8,1.3]*default value

Single Control Policy Handles Varying Conditions

Controller is **robust** to varying conditions:

- a) Healthy human
- b) Human with weak muscles
- c) Human with left hemiparesis



- Shuzhen Luo, Androwis Ghaith, Adamovich Sergei, Erick Nunez, **Hao Su**, and Xianlian Zhou. "Robust Walking Control of a Lower Limb Rehabilitation Exoskeleton Coupled with a Musculoskeletal Model via Deep Reinforcement Learning (under review)"

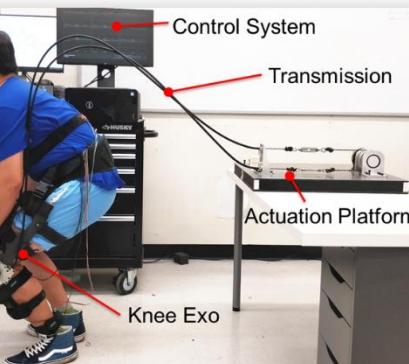
Soft Robots for and as Medicine to Empower Humanity

Hao Su

Director of Lab of Biomechatronics and Intelligent Robotics

<https://haosu-robotics.github.io>

Mechanical and Aerospace Engineering
North Carolina State University (NCSU)



CAREER, NRI, CPS
Future of Work



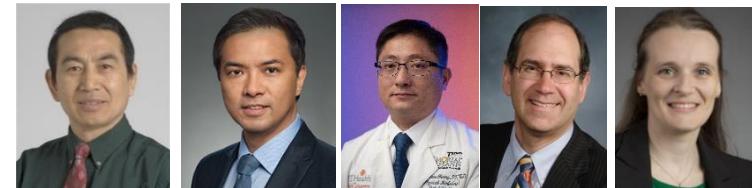
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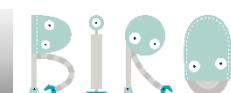
Carnegie
Mellon
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mobility
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Biomechatronics and
Intelligent Robotics (BIRO) Lab