Learning in Simulation for Exoskeleton-Assisted Versatile Walking in Community Settings

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***Abstract*— Exoskeletons have the potential to improve human mobility. However, the development of existing controllers of exoskeletons requires either lengthy human testing or complicated handcrafted control laws to assist versatile walking. We proposed a data-driven and physics-informed reinforcement learning method to address these challenges. Our controller was trained solely in simulation, deployed directly to the exoskeleton, and reduced 24.3% metabolic costs for walking. Our method opens new frontiers in wearable robots to harness the power of learning and simulation to improve human mobility.**

I. Introduction

Exoskeletons have the potential to assist humans in walking. However, existing methods require either hours-long human testing to identify the optimal assistance profile or complex handcrafted control laws to adapt to different locomotion [1]. Our previous work [2] used reinforcement learning to train a controller for walking assistance but its performance was only evaluated in numerical simulations. Here we proposed a data-driven and physics-informed reinforcement learning framework to address these challenges. Our method eliminated the need for human testing and was trained entirely in simulation. Yet, it can be directly deployed to a hip exoskeleton and produce an immediate reduction in metabolic cost for walking at different speeds.

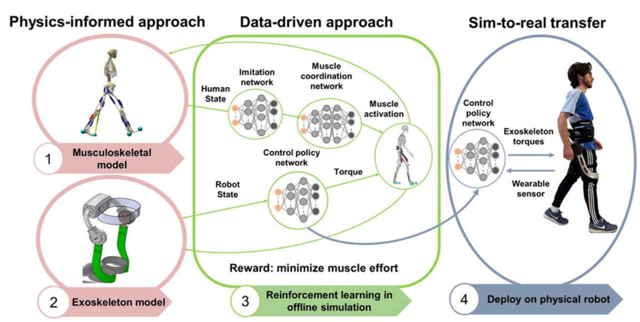

Fig. 1. Data-driven and physics-informed reinforcement learning framework to learn a controller from simulation that assists various activities. The trained controller can be seamlessly deployed on the physical exoskeleton and produce immediate energy reduction.

II. Methods

Our proposed method contains two parts: data-driven approach and physics-informed approach. For the data-driven approach, we used 3 interconnected neural networks with more than 2000 neurons (Fig. 1) to simulate the human musculoskeletal response to exoskeleton assistance. For the physics-informed approach, we incorporated a whole-body musculoskeletal model with 208 muscles and 52 DoFs, physical model of the hip exoskeleton, and bushing element to account for human-robot interaction. The three neural networks were trained simultaneously to generate a controller for walking at different speeds.

III. Results And Discussions

We evaluated the performance of the trained controller on 8 able-bodied subjects (5 males, 3 females) for walking at 1.25 m/s. Results showed that the controller immediately reduced the metabolic cost for each activity by 24.3% (Fig. 2), which is the largest reduction among existing literature using either tethered or portable lower-limb exoskeletons. Our controller also generated continuous torque assistance profiles automatically during speed changes, indicating its superior capability to assist versatile human walking.

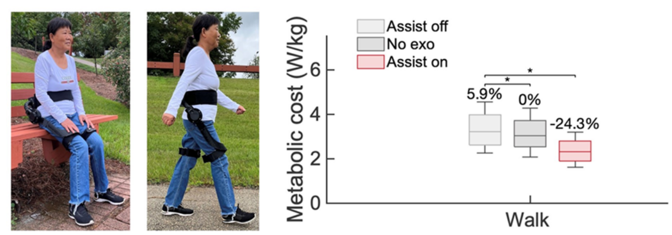

Fig. 2. Our controller reduced 24.3% metabolic rate in Assist on mode compared with No exo mode for people (n=8) walking at 1.25 m/s. This is the largest reduction among all other existing lower-limb exoskeletons.

IV. Conclusions

We demonstrated that a controller trained completely in simulation can be deployed directly onto a physical robot and produce an immediate reduction in energy for versatile walking. This opens up a new frontier in wearable robots to harness the amazing power of learning, physics, and simulation to improve human mobility and benefit people in community settings.

References

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