Robust Neural Network Controllers for Lower Limb Exoskeletons: A Deep Reinforcement Learning Approach

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Abstract— **In this study, we introduce a novel deep reinforcement learning (DRL) based approach for controlling lower limb rehabilitation exoskeletons (LLREs). Our method employs a neural network-based controller that accurately forecasts real-time commands for the exoskeleton's actuators using only proprioceptive signals from the LLRE. This controller is trained within a sophisticated virtual simulation environment integrating a comprehensive human musculoskeletal model and an exoskeleton interaction model. To enhance adaptability, we utilized domain randomization during training to simulate diverse patient musculoskeletal conditions. We validate the effectiveness and robustness of our DRL-based LLRE controller across various neuromuscular conditions during walking, evaluating key metrics such as stability and gait symmetry. This innovative approach supports seamless deployment of trained controllers onto physical hardware through sim-to-real transfer, eliminating the need for patient-specific experimentation and parameter tuning. Our work represents a significant advancement in LLRE control methodology, promising enhanced functionality and adaptability for real-world applications.**

I. INTRODUCTION

Lower limb rehabilitation exoskeletons (LLREs) with multi-joint actuation are increasingly used in clinics to enhance mobility for individuals with diverse neuromuscular disorders, such as muscle weakness or paralysis [1]. Ensuring robustness and stability in LLREs for walking assistance is crucial for patient safety. Many current LLREs require additional support like crutches or supervision from a healthcare provider to prevent falls during locomotion. Some autonomous LLREs, such as Rex (Rex Bionics) and Atalante (Wandercraft), offer independent walking capabilities but often at the cost of slower speeds and increased weight. Enabling autonomous locomotion with LLREs can significantly boost patient confidence in clinical and home settings. Advanced controllers that robustly manage walking assistance under various human-exoskeleton interaction conditions are needed to achieve this goal.

Current LLRE controllers often prioritize trajectory tracking, which is essential in early-stage rehabilitation when patients have limited muscle strength. However, these controllers typically require laborious task-specific fitting and parameter tuning. In this study, we introduce a deep neural network-based reinforcement learning (RL) controller for LLREs that achieves robust walking control without the need for parameter tuning. Our controller is trained exclusively from simulations involving human-exoskeleton interactions, using only proprioceptive signals from the LLRE. This approach simplifies the deployment of the controller onto physical exoskeletons.

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II. MATERIAL AND METHODS

A. Simulation of Human-LLRE Interaction

A LLRE hardware shown in Fig. 1 has been developed to assist patients with gait rehabilitation [2]. This LLRE system has 8 total actuated DoFs, and each side includes 1 DoF for the hip flexion/extension, 1 DoF for the knee flexion/extension, and 2 DoFs for the ankle (dorsiflexion/plantarflexion and inversion/eversion). The actuators can generate torques over $160Nm$ per DOF [3]. The total mass of the exoskeleton is 20.4kg and the frame of the exoskeleton was 3D printed with reinforced carbon fiber between layers. To simulate realistic human exoskeleton interaction, a full-body human musculoskeletal model [6] was integrated with the LLRE to create realistic human-exoskeleton interaction forces and constraints. The muscles were modeled with a Hill-type model to generate forces and act on the bones through each muscle's origin and insertion points. The LLRE has straps around the hip, femur and tibia to constraint the human motion, with force interaction simulated with linear bushing elements [4].

B. Learning Framework

Our innovative deep neural network and RL-based robust controller for LLREs utilizes a decoupled offline human-exoskeleton simulation training with three independent neural networks (as shown in Fig. 1A-B). Each network is modeled as a Multi-Layer Perception (MLP). The exoskeleton controller is driven by a MLP control policy (the motion imitation network in the figure) that acts on a stream of the LLRE's proprioceptive signals, including joint kinematic states (e.g. from joint encoder data), and subsequently predicts real-time position control targets for the actuated joints. The control policy are trained with rewards including tracking of a provided normative walking trajectory that is crafted for this LLRE. Two other neural networks are connected with the control policy to predict the interaction forces and muscle coordination. To further increase the robustness of the control policy against different human conditions, domain randomization are employed during training that includes not only randomization of exoskeleton dynamics properties but,

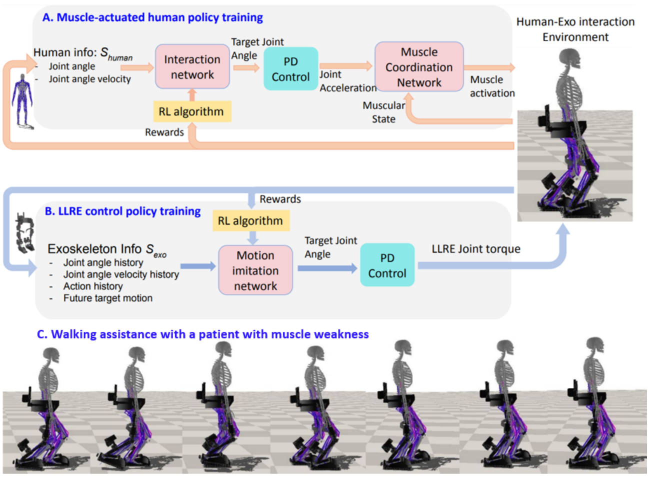

Fig. 1. A-B: Overview of the modular, decoupled RL-based walking control framework of the LLRE with human-in-the-loop. C: Snapshots of a walking motion with LLRE assistance for a subject with muscle weakness, displaying muscle activation in color.

more importantly, randomization of human muscle strength to simulate the variability of the patient's disability. For examples, muscle weakness are modeled by reducing all muscles' maximum isometric force (strength) by half. Left Hemiplegia and quadriplegic conditions are modeled by vanishing the active forces of the muscles on the left side and both sides, respectively. Through this decoupled deep reinforcement learning framework, the trained controller of LLREs offers the potential to provide reliable walking assistance to human with different degrees of neuromuscular disorders without any control parameters tuning.

III. Results

Our learned controllers of the LLRE was able to perform balanced walking motion autonomously with subjects of different muscular conditions, including healthy individuals and those with passive or quadriplegic muscles, muscle weakness, and left hemiplegia. In Fig. 1C, a predicted walking motion with LLRE assistance for a subject with muscle weakness is shown. To demonstrate the robustness of the controller, we conducted statistics analysis of walking under these four human conditions with 100 walking gait cycles each. The root mean square error (RMSE) of joint tracking accuracy for the hip, knee, and ankle angle are all within 5.3 degrees. We used a symmetry index $R = X_R/X_L$ to qualify the gait symmetry between the right and left legs, with X_R and X_L denoting the mean joint angles of the right leg and the left leg, respectively. The symmetry index of the hip, knee, and ankle flexion angles all stayed within 0.82 and 1.12, except for the hip (1.49) in the left hemiplegia condition. We further compared controllers trained with and without muscle strength randomization, evaluated over 100 walking trials (40 cycles each) for each of the four conditions. With muscle randomization, the controller showed significantly higher success rates (SR) of maintaining balance on all conditions than that trained without muscle strength randomization.

IV. Discussion

Our method trains the LLRE controller from decoupled offline human-exoskeleton simulations and this decoupled structure enables the trained control policy to use only proprioceptive information of the LLRE to predict control commands. This consequently facilitates straightforward deployment of the controller to the physical exoskeleton. After acquiring a trained parameter set (weights and bias) of the MLP control policy from deep reinforcement learning, we can deploy the controller to the physical LLRE system. We can build the same MLP in Matlab and load the trained parameter set and then utilize the Matlab program to interface with the hardware and activate the neural network for control. The Matlab program will use a low-level torque control architecture composed of an inner-loop current control and an outer-loop torque control with various feedback signals.

V. Conclusion

A universal, RL-based walking controller was trained and virtually tested on a LLRE system to verify its effectiveness and robustness in assisting users with different disabilities such as passive muscles (quadriplegic), muscle weakness, or hemiplegia conditions without any control parameters tuning. The decoupled network structure allows us to isolate the LLRE control policy network for testing and sim-to-real transfer since it uses only proprioceptive information of the LLRE (joint sensory state) as the input. This RL training framework can be extended for other activities such as squatting [5] and sit-to-stand due to it motion imitation capability. It can also be extended to develop controllers tailored for patients with other pathologic conditions such as muscle contracture, spasticity, cerebral palsy, potentially requiring further adjustment or randomization of muscle parameters such as optimal fiber lengths or muscle contraction intensity for spasticity.

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