Imitation Learning for Adaptive Control of a Virtual Soft Exoglove

Shirui Lyu[1], Vittorio Caggiano[2], Matteo Leonetti[1], Dario Farina[3], and Letizia Gionfrida[1,4]

***Abstract*— The use of wearable robots has been widely adopted in rehabilitation training for patients with hand motor impairments. However, the uniqueness of patients' muscle loss is often overlooked. Leveraging reinforcement learning and a biologically accurate musculoskeletal model in simulation, we propose a customized wearable robotic controller that is able to address specific muscle deficits and to provide compensation for hand-object manipulation tasks. Video data of a same subject performing human grasping tasks is used to train a manipulation model through learning from demonstration. This manipulation model is subsequently fine-tuned to perform object-specific interaction tasks. The muscle forces in the musculoskeletal manipulation model are then weakened to simulate neurological motor impairments, which are later compensated by the actuation of a virtual wearable robotics glove. Results shows that integrating the virtual wearable robotic glove provides shared assistance to support the hand manipulator with weakened muscle forces. The learned exoglove controller achieved an average of 90.5% of the original manipulation proficiency.**

I. INTRODUCTION

The use of wearable robots has shown promising potential both in neurological rehabilitation protocols [1] and in passive supports to boost neural motor performance [2]. Patients with upper limb neurological dysfunctions or impairments often experience varying degrees of dexterity loss [3]. A personalized rehabilitation strategy is essential to enhance their independence, thereby improving their quality of life [4]. However, designing a tailored rehabilitative intervention that accounts for rapidly changing, patient-specific clinical indicators [5], particularly through wearable robotic devices, remains a significant challenge.

One of the challenges in realizing an intelligent controller for assistive wearable robots is the translation of the unique medical conditions of individual patient into adaptable controllers. For example, patients recovering from ischemic or hemorrhagic strokes, often experience significant limitations in their range of motion, characterized by symptoms such as reduced muscle strength or limitation of range of motion [6]. In clinical settings, such diverse medical conditions are typically managed through ad-hoc manual rehabilitation programs administered under the supervision of trained professionals [4]. However, in the context of wearable robotic rehabilitation, the device controller needs to be timely adjusted to provide clinical support [7], [8]. The development of automated methods for adapting wearable device control to individual patient needs is crucial for enabling personalized and accessible rehabilitation interventions.

Data-driven control approaches for wearable robotics have become widely adopted, enabling more general and accessible solutions for wearable robotic control [9]–[14]. These approaches learn biological features of the user such as kinematics, and muscle dynamics, from sufficient data to control the assistive devices. However, they focus on general rather than specific user behaviours, thus leaving a gap in addressing practical individual-based rehabilitation needs.

The development of personalized control strategies for wearable robots has been employing musculoskeletal models to facilitate adaptable controller training through Reinforcement Learning (RL) [15], [16]. Despite their utility, these approaches often yield non-intuitive behaviours [17] attributable to the absence of reliable human-reference data. To address these limitations, the integration of vision and imitation learning within RL training frameworks offers a promising solution. These methods enhance the fidelity of natural human behaviour modelling by providing enhanced biomechanical insights.

In this work, we propose a framework that uses imitation learning to derive user-specific reference trajectories from a healthy subject's video dataset [18]. These trajectories are used to reconstruct kinematics and muscle dynamics in silico, where hand impairments are simulated. Finally, a tendon-driven exoskeleton glove (exoglove) control strategy that adapts to the simulated impairments is tested using the healthy reference as a basis for optimization reference.

The proposed approach consists of three stages (Fig.1). First, reference trajectories are extracted from video data and learned by imitating the behaviour of a healthy subject through *MyoHand* [19], a biologically accurate musculoskeletal hand model, to replicate the user's natural behaviour. Second, RL-driven manipulation is applied to simulate hand-object manipulation tasks within the musculoskeletal model, and then a simulated impairment is incorporated to reflect reduced functionality in the hand. Finally, a virtual exoglove, modeled after a real device [20], is implemented in simulation, where an adaptive control strategy is developed to compensate for the impaired hand, optimizing hand-object manipulation and improving functionality for the impaired hand.

*This work was supported by The Royal Academy of Engineering Research Fellowship (RF2324-23-229).

[1]S. Lyu, M.Leonetti and L. Gionfrida are with the Department of Informatics, King's College London, London, WC2R 2LS, UK. (shirui.lyu, matteo.leonetti, letizia.gionfrida)@kcl.ac.uk

[2]V. Caggiano is with MyoLab, New York, USA and Harvard Medical School and Spaulding Rehabilitation Hospital, Boston, USA caggiano@gmail.com

[3]D. Farina is with the Department of Bioengineering, Faculty of Engineering, Imperial College London, London, SW7 2AZ, UK d.farina@imperial.ac.uk

[4]L. Gionfrida is also with John A. Paulson School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA.

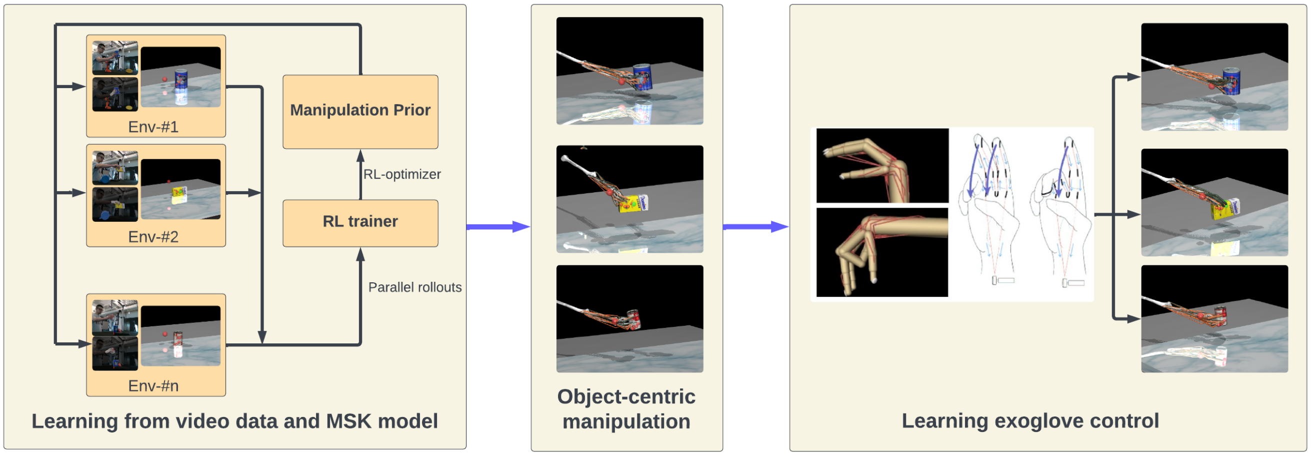

Fig. 1. Pipeline overview illustrating the three main stages: (1) extraction of user behavior via imitation learning from healthy subject video data, (2) training a biologically accurate musculoskeletal hand model for object-centric manipulation and simulating muscle impairments, and (3) development and testing of a tendon-driven exo-glove controller to compensate for impaired hand functionality.

II. Related Work

A. Learning manipulations from human videos and RL

As human video inherently captures the intricate kinematics of hand-object interactions, including the complexity and precision required for dexterous manipulation, extensive research has focused on understanding and modeling these interactions [18], [21]–[23]. Those recorded interactions provide sufficient context for the understanding of dexterous manipulation and facilitate other robotics applications such as handling previously unseen manipulation tasks [24]. Nevertheless, the learned model, referring to computational models trained on human video data to predict or replicate manipulation strategies, depends heavily on human video data and is less robust in handling unseen objects.

RL-based manipulation, on the other hand, is often data-inefficient and explores solutions with computational resources over data. Such an approach gives rise to manipulation understanding that is less relevant to human demonstrations. Object-centric approaches [25], [26], for example, mainly match the object in hand with a reference trajectory, and learn a manipulation strategy even with a high Degree of Freedom (DoF) musculoskeletal hand model.

Recent work [27]–[29] has attempted to combine the advantage from both sides: by using human demonstration video to facilitate RL training, and by using RL to train robust grasping behaviours. In addition, Wan et al. [30] leveraged RL and computer vision to first generate multiple grasping gestures before applying conditioned policy training to achieve generalized grasping behaviour. Chen et al. [17] proposed to use of human demonstration video to guide the RL training while leaving space for RL exploration to handle robot-object interactions. However, most previous works generalize the grasping behaviour and few of the studies were conducted on model-based RL for rehabilitative robotics applications.

B. Model-based wearable robotics control

Recent studies [10], [12], [14], [31], on wearable robotics systems, have focused on integrating high-level task control with low-level hardware control to enhance system performance. This combined approach allows wearable robots to execute tasks more effectively while adapting to the mechanical and dynamic constraints of the hardware. Introducing high-level perceptual information such as egocentric views [32], [33], or user-intent [15], into the control architecture usually improves the system's responsiveness and adaptability. However, deriving accurate and reliable perceptual information requires meticulous modelling of biological states. These models must be biologically accurate to ensure that the system's responses align appropriately with the user's physiological and cognitive conditions, thereby enhancing the overall efficacy and safety of the wearable robot. Hodossy and Farina [15] proposed to use a humanoid model and motion tracking to learn a robust locomotion model to inform the training of an intention-aware prosthesis. Luo et al. [16] leveraged a human musculoskeletal model to train an exoskeleton to provide locomotion support based on the user states. However, few studies have focused on upper-limb wearable robotics aimed at providing shared assistance through musculoskeletal hand models.

III. Methodology

Our approach consists of three main stages. First, we learn the user's behavior context by extracting joint kinematics from a video dataset [18] of a healthy subject. Second, a biologically accurate musculoskeletal hand model is trained for object-centric manipulation tasks, enabling the simulation of hand-object interactions that reflect the user's behaviour. In this stage, the model is also adapted to simulate a designated muscle-weakened hand impairments. Lastly, a tendon-driven soft exoglove is applied to the musculoskeletal hand, with an RL-based glove controller, to support dexterous manipulation