5. Project Description

Objectives of the project

Background

Exoskeletons have shown promise in assisting human mobility across a range of scenarios, such as supporting coordination for hemiplegic patients, assisting movement during physical rehabilitation, enabling paralyzed individuals to walk again, and even enhancing endurance during demanding activities like hiking or climbing. To achieve such supportive effects, various modeling approaches have been employed, including analytical mathematical models, machine learning-based models, and highly nonlinear deep learning models. The assistance performance of the exoskeleton has proven to be excellent; however, achieving such effectiveness still requires careful personalization for each individual.

Problem

Due to diversity in human physiology and locomotion environments, it takes a long time, large amounts of data, and considerable effort to personalize the exoskeleton model, regardless of the modeling approach used. The user needs to spend a high cost of time to provide the information. This is the main reason why most people hesitate to use exoskeletons in their life, even though they offer significant support. If we want to make exoskeletons a device that everyone can benefit from, it is necessary to collect data across a wide range of unexpected and critical situations. However, acquiring such data remains a significant challenge—yet it is essential for making the exoskeleton model personalized enough to satisfy each user's requirements.

Solution

Our system provides an automated tuning environment (**Figure 1**) to reduce the time consumption of personalizing exoskeleton models. To eliminate the discomfort of wearing sensors and specialized suits, we develop a markless motion capture system (MOCAP, https://www.youtube.com/watch?v=za70fA9GLbw). Based on our MOCAP, the data collection process is not only fast and convenient but also capable of capturing fine-grained kinematic parameters of the user. Following this, our system leverages digital twins technology: by constructing a user-specific neuro-musculoskeletal (NMS, https://www.youtube.com/@hip_exo) model in simulation, we can synthesize physiological data across various scenarios and environments—such as stair climbing, running, everyday walking, or even falling. Another simulated model, including both the hardware and software aspects of the exoskeleton, will learn to minimize human-machine interaction (HMI) obstruction through simulated collisions. The information generated from this process will be transmitted via a virtual interface that mirrors the real-world exoskeleton software, ultimately producing a model that has adapted to the user's habitual movement patterns. Once this personalized exoskeleton model is complete, it can be updated to the real exoskeleton The user can immediately benefit from this exoskeleton model, which is ready to assist with a variety of daily tasks and movement needs.

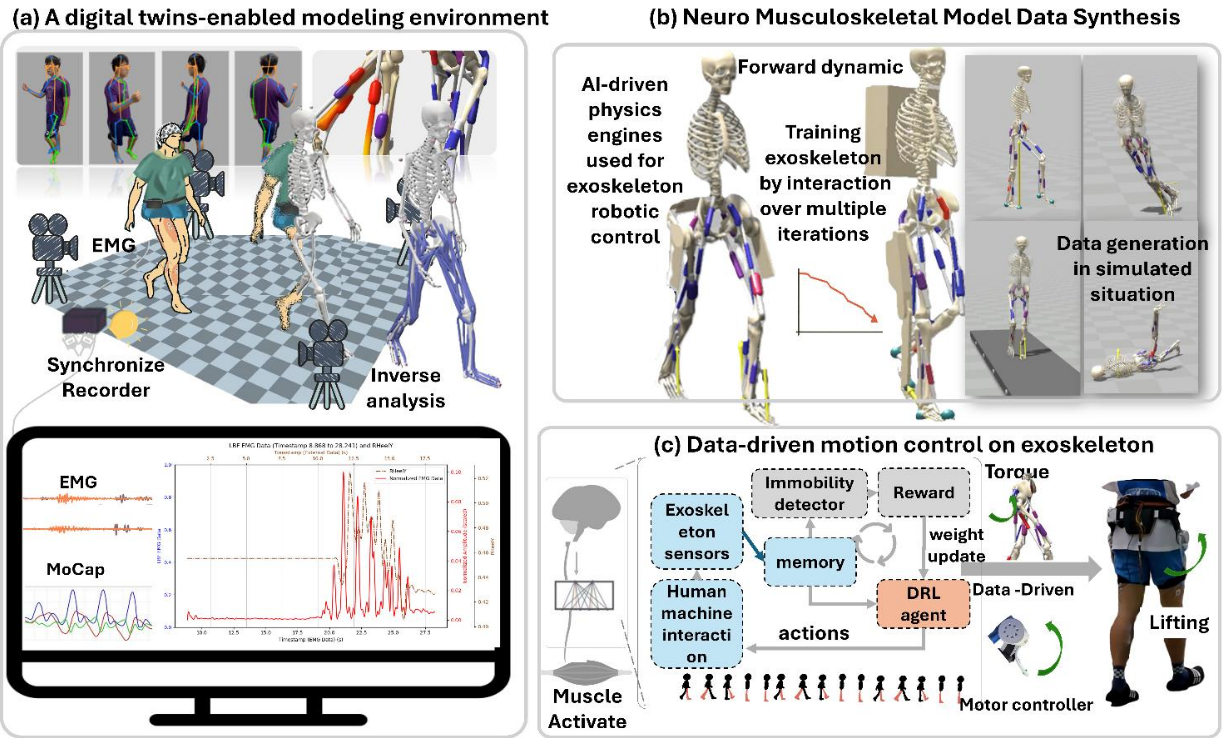

Figure 1. Overview of personalized neuro-muscular exoskeleton control system. (a) A digital twins-

enabled modeling environment. Through MOCAP and inverse analysis, an NMS model that matches the subject's fully NMS characteristics, and the movements are reconstructed on this digital twins. (b) NMS Data Synthesis. Subject movement data that was not recorded can be synthesized under different simulated scenarios in simulation. (c) Data-driven coordination of motion control on exoskeleton. Deep Reinforcement Learning (DRL) is the core of our data-driven model training framework. Once trained, the model can be deployed to real hardware.

Material and Methods

We propose a personalized digital twin modeling pipeline for exoskeleton adaptation, in which a NMS model is constructed based on our MOCAP system. Electromyography (EMG) recordings are also collected for one-time calibration of muscle activation parameters (**Figure 2**).

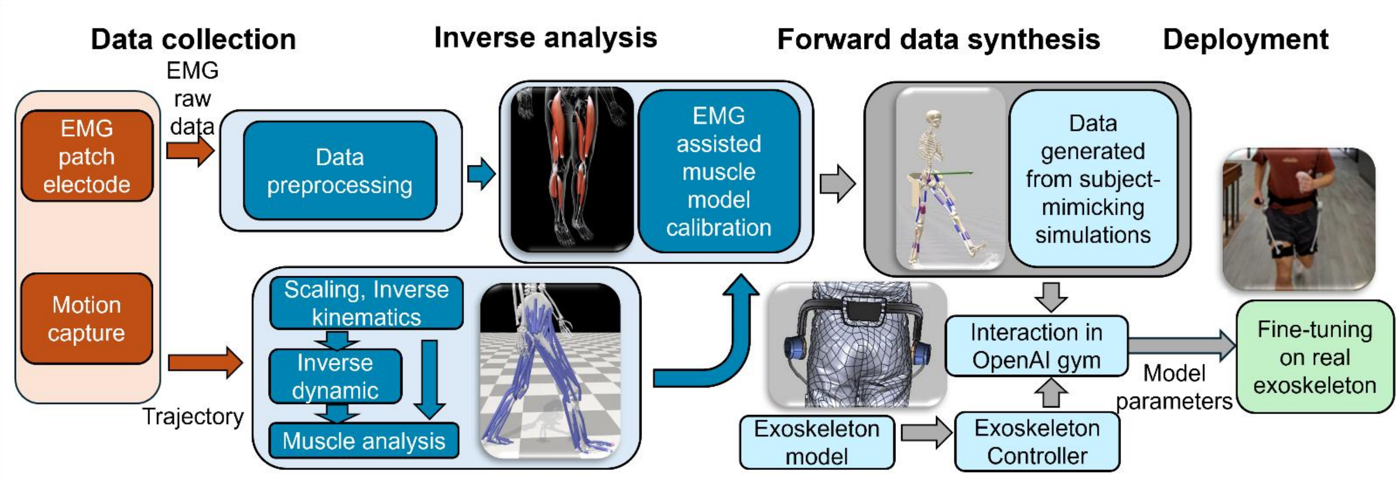

Figure 2. Pipeline of building the subject's digital twins and deploying it to an Exoskeleton. First, data are captured using MOCAP and EMG. Second, inverse analysis personalizes the musculoskeletal model. Third, forward dynamic simulations generate diverse movement data to train the exoskeleton controller Finally, the trained controller is deployed on a real exoskeleton for real-world assistance.

Data collection

In this stage (**Figure 3**), the user's joint angles, velocities, and trajectories are recorded using MOCAP. At the same time, EMG signals are recorded through surface electrodes, which are required only once for the calibration of muscle model parameters.

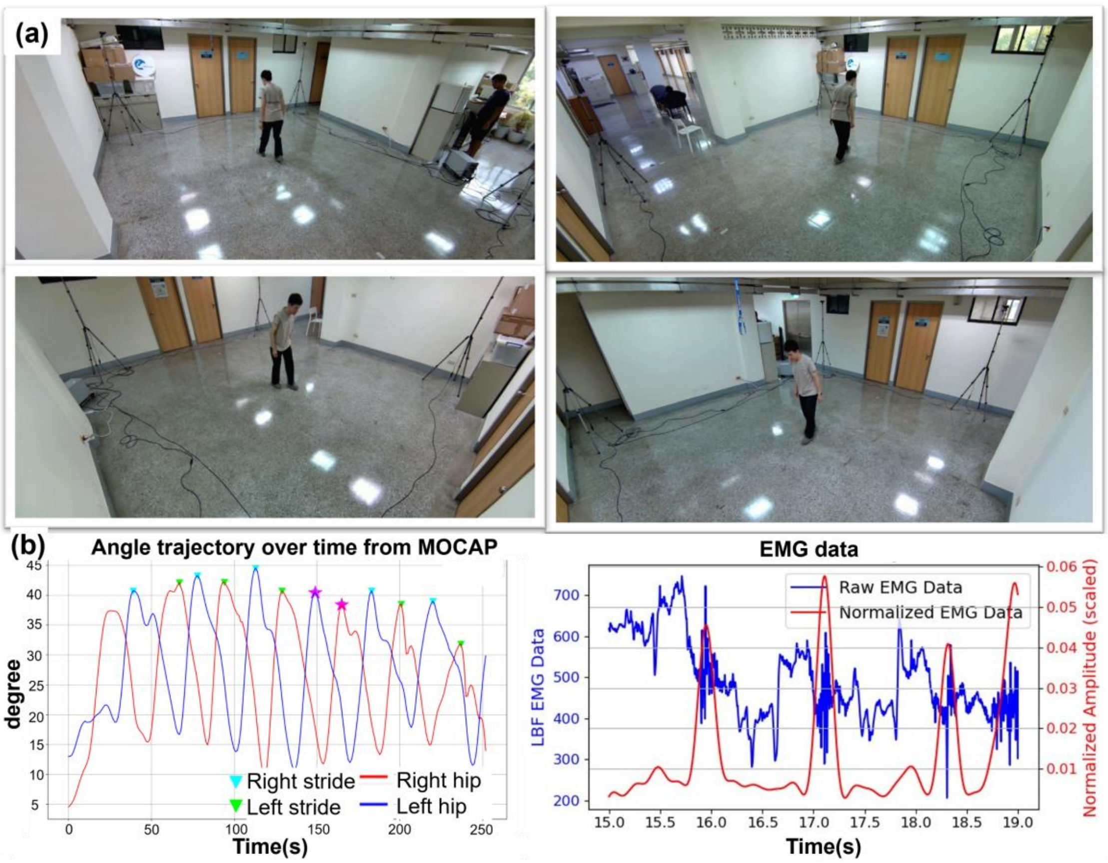

Figure 3 MOCAP data collection. (a) walking trials captured using our MOCAP. (b) data collected from our system through reinforcement learning for adaptive control.

Inverse analysis

Inverse analysis scales a generic model to the subject's biomechanics, estimating joint torques and muscle forces via inverse dynamics, muscle analysis, and EMG-assisted modeling is utilized to merge the motion and EMG outcomes (**Figure 4**).

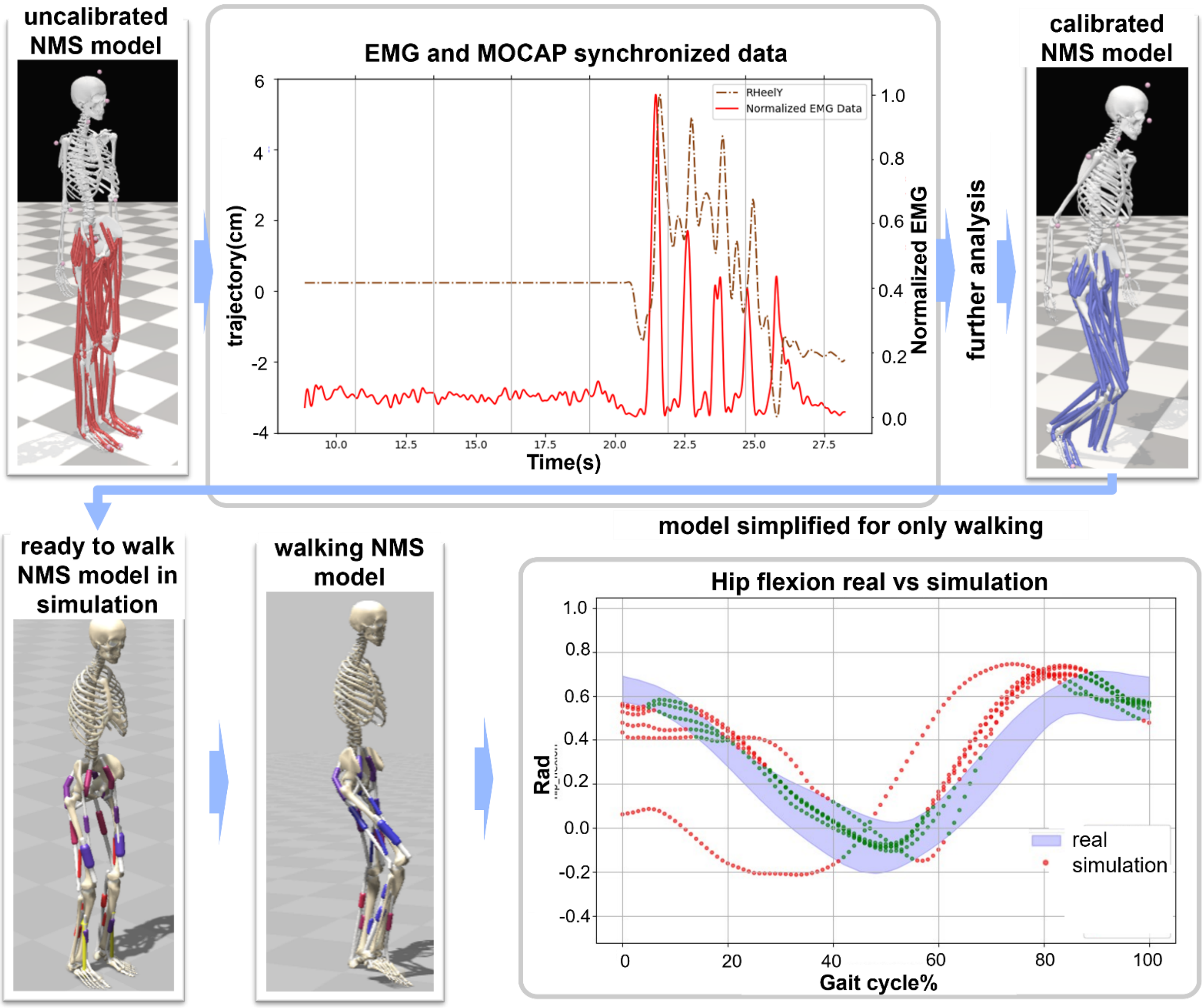

Figure 4 EMG and MOCAP as inputs for personalized NMS model calibration

Forward data synthesis

We extend the model using forward dynamics to synthesize training data for different motion scenarios. This framework potentially lays the groundwork for what could be considered a virtual cerebellum. Importantly, the virtual environment, in turn, allows us to analyze this agent from a top-down, omniscient perspective, providing insights that are difficult to obtain in real-world settings—such as ground reaction forces (GRFs) (**Figure 5**). The DRL framework teaches the model to optimally assist the user while preventing unexpected falls caused by exoskeleton misalignment, abrupt halts, and other disturbances. After training, the exoskeleton-assisted NMS model achieves stable walking.

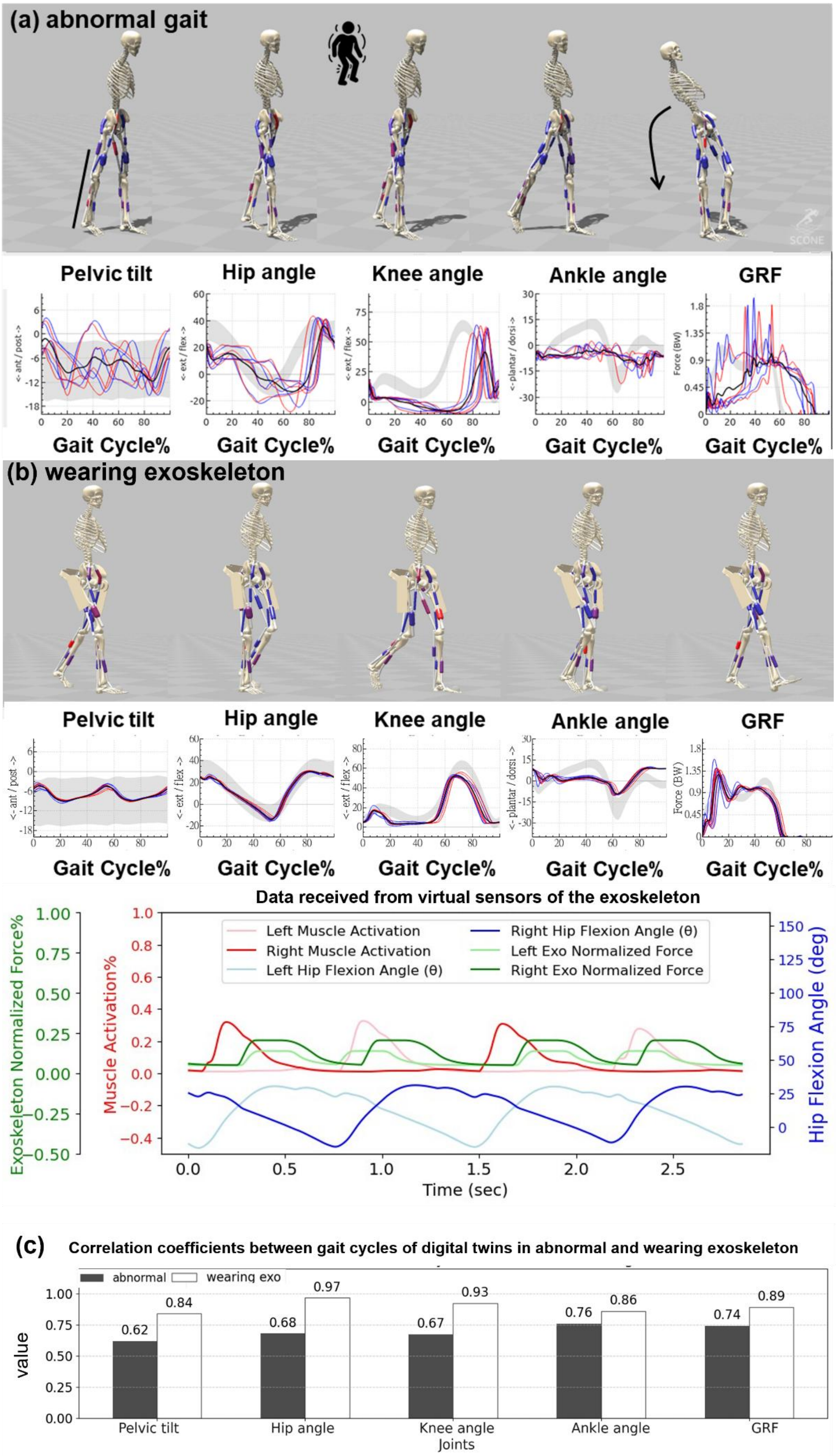

Figure 5. Model personalization in simulation. (a) Abnormal gait shows initial knee stiffness, delayed movement, large step variability, and ends in a fall. (b) Wearing an exoskeleton improves gait stability significantly. The exoskeleton receives data in a virtual sensor that mirrors what would be obtained from a real exoskeleton, enabling a smooth transition from simulation to reality. (c) We use correlation coefficients to quantify the differences between gait cycles digital twins in abnormal and wearing exoskeleton.

Deployment

After training, the controller is deployed on the exoskeleton hardware and fine-tuned during real-world use if still needed (**Figure 6**).

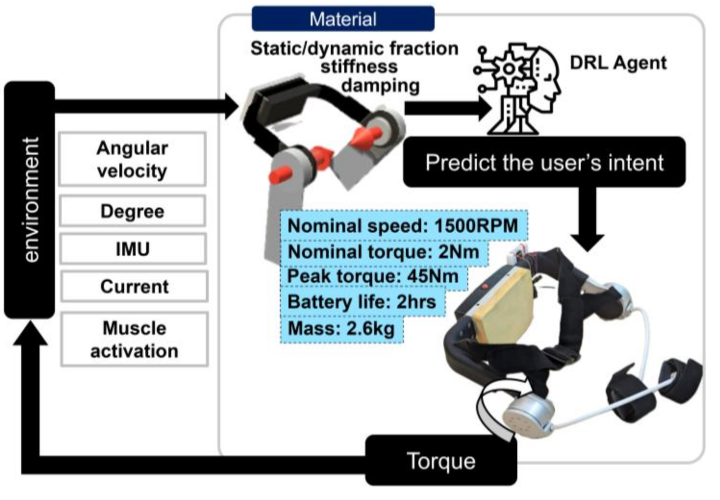

Figure 6 Exoskeleton from simulation to real. The simulation shares identical inputs, outputs, and material properties with the real exoskeleton, enabling rapid and reliable sim-to-real transfer.

Preliminary Results

We have preliminarily verified the system's ability to provide personalized gait prediction and assistance for a user who occasionally experiences stiffness in one leg through a series of modeling (**Figure 7**). We returned to MOCAP environment to verify the difference between the model's assistive performance before and after personalization as shown in **Figure 8**. Joint angle control becomes more precise, muscle effort is reduced, and the user can climb stairs without relying on handrails—highlighting the significant improvements achieved through individualized adaptation.

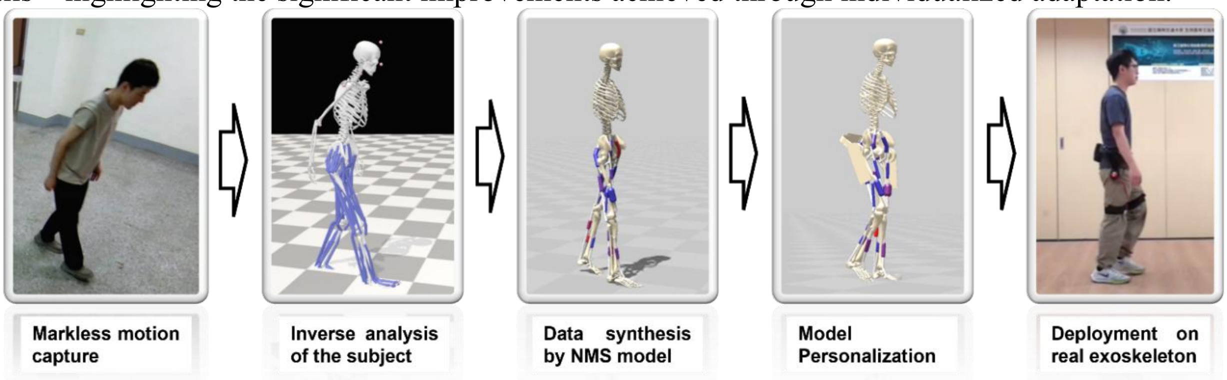

Figure 7 Implementation of a Personalized Solution Pipeline.

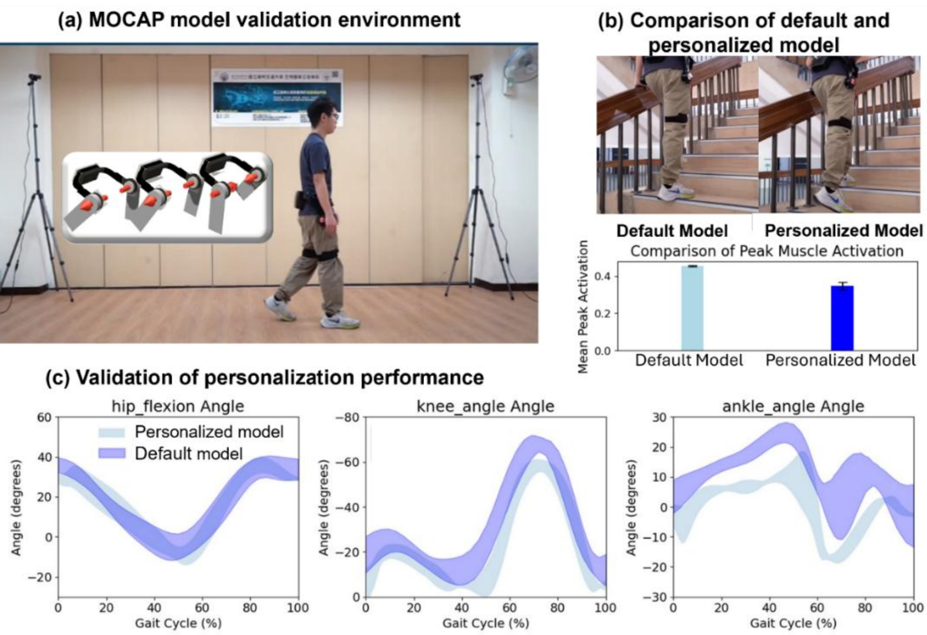

Figure 8. Validation and Comparison of Default vs. Personalized Models. (a) The MOCAP system is also used as a validation environment to assess model accuracy. (b) A clear example is observed during stair climbing: the default model required hand support, while the personalized model adapted well to the terrain. The reduction in peak muscle activation further demonstrates improved biomechanical efficiency. (c) Inverse kinematics analysis shows that the personalized model enables more fine-grained joint coordination than the default model, resulting in gait patterns that better reflect individual movement habits.