# Data-Driven Impedance Control for Lower-Limb Exoskeletons Assisting Five Ambulation Modes

Clément Lhoste[1†], Alberto Cantón[1,2†], Emek Barış Küçüktabak[1,3], Matthew R. Short[1,4], Rebecca Schwanemann[1], Shoshana Clark[1], Jesús Tornero[2‡], Lorenzo Vianello[1‡*], José Pons[1,3,4‡]

[1*]Legs and Walking Lab, Shirley Ryan AbilityLab, 355 E Erie St, Chicago, 60618, IL, USA.
[2]Center for Clinical Neuroscience, Hospital Los Madroños, M-501, Km 17, 900, Brunete, 28690, Madrid, Spain.
[3]Center for Robotics and Biosystems, Northwestern University, 633 Clark St, City, 60208, IL, USA.
[4]Department of Biomedical Engineering, Northwestern University, 633 Clark St, City, 60208, IL, USA.

*Corresponding author(s). E-mail(s): iiauthor@gmail.com;
Contributing authors: iauthor@gmail.com; iauthor@gmail.com; iiauthor@gmail.com; iiauthor@gmail.com; iiauthor@gmail.com; iiauthor@gmail.com; iiauthor@gmail.com; iiiauthor@gmail.com;
†Clément Lhoste and Albero Cantón contributed equally to the authorship of this manuscript.
‡ Jesús Tornero, Lorenzo Vianello and José Pons contributed equally to the conception and scientific supervision of this study and the authorship of this manuscript.

**Abstract**

**Proposal for Journal of NeuroEngineering and Rehabilitation**
**Background:** State-machine-based control for lower-limb exoskeletons requires long calibration, as many parameters need to be tuned to provide appropriate assistance in different activities (walking, climbing up and down ramps and stairs). The purpose of this study is to reduce the number of these parameters, to achieve a simpler control framework.

**Methods:** Our control method leverages impedance control, where notably equilibrium angles are automatically extracted from a benchmark dataset of able-bodied gait across various terrains. The efficacy of the proposed controller, with respect to transparent control, is assessed through experiments with 14 healthy individuals walking in the aforementioned five conditions. Net Power metrics, as well as kinematic analysis, are employed to evaluate the effectiveness of the exoskeleton's assistance.
**Results:** Results showed a statistically significant reduction in net interaction power with the state-machine controller across all ambulation modes ($p < 0.05$), indicating greater user assistance. Preferred walking speed was notably faster with the state-machine controller, particularly on level ground and ramps (22-25% increase). Kinematic analysis revealed closer alignment to able-bodied gait patterns with the state-machine controller, suggesting improved gait quality.
**Conclusion:** The abstract serves both as a general introduction to the topic and as a brief, non-technical summary of the main results and their implications. The abstract must not include subheadings (unless expressly permitted in the journal's Instructions to Authors), equations or citations. As a guide the abstract should not exceed 200 words. Most journals do not set a hard limit however authors are advised to check the author instructions for the journal they are submitting to.

**Keywords:** keyword1, Keyword2, Keyword3, Keyword4

# 1 Introduction

Lower-limb exoskeletons have the capability to aid individuals with impairments in their daily activities and to support physical rehabilitation in clinical settings [**? ?** ]. Moreover, there is a growing trend in using these exoskeletons to augment the abilities of individuals who do not have impairments [**?** ]. In particular, weight-bearing exoskeletons, which cover the entire lower extremities, include rigid robotic components that enable multi-joint support and direct transfer of loads to the ground.

Typically, the control of the interaction between a user and exoskeleton adopts a hierarchy of control levels: high-level, mid-level, and low-level [**? ?** ]. For lower-limb exoskeletons, the high-level controller calculates the desired behaviour tailored to specific ambulatory activities, such as walking on flat terrain, stairs or ramps. The role of the mid-level controller is to estimate the various states within an activity, for example, identifying the gait states (e.g., swing and stance) during walking and setting a desired interaction torque behavior accordingly. Interaction behavior is typically modeled using virtual spring damping attached to reference joint positions. These spring-damping behaviors are characterized by stiffness and damping parameters. Finally, the low-level controller is responsible for compensating the exoskeleton's dynamics and generating motor commands, based on the desired interaction torque profile identified by the mid-level controller.

The variability of everyday life demands these devices to perform numerous locomotion modes (such as stairs, ramps, overground walking). At the same time, these locomotion modes may vary in their characteristics (ramp incline, stair height, and walking speed). All these features require the identification of controls for the exoskeleton that are specific to each activity. Additionally, each individual user may have particular needs. All of this drastically impacts the time required for calibrating assistive device controllers. This problem has been extensively observed for active prosthetic devices[**?** ]. For example, a 2DoF impedance controller required a total of 140 tunable parameters for five ambulation modes. While only a portion of these parameters were considered necessary to tune, the device's configuration and tuning still required the researchers up to five hours to complete.

For LL prosthetic devices, solutions have been proposed using simulation enviromnent and adaptive controllers [**?** ], reinforcement learning [**? ?** ]. Other studies suggest that benchmark datasets of healthy individuals can be used to extract parameters for use in WR control. [**?** ] proposed a DNN model trained on gait trajectories of intact limb individuals [**?** ] applied to control the prosthetic leg without post-tuning the network. [**?** ] presents a data driven, phase-based controller for variable-task walking that uses continuously-variable impedance control during stance and kinematic control during swing to enable biomimetic locomotion. These parameters are calculated using an optimization method that fit with a dataset [**?** ] of healty individuals performing the different tasks.

In the field of lower limb exoskeletons, there is a groving interest in their rehabilitation application [**? ? ?** ]. Nevertheless, few studies have presented the calibration time and procedure. This may be attributed to the use of pre-set trajectories and the lack of compliance, which eliminates the need for calibrating stiffness and damping components. Moreover, their application is typically limited to overground walking, with few studies performed on stairs and ramps. Finally, these devices exhibit substantial differences compared to active lower limb prosthetics. Firstly, they may require an active role from the user in the joints where they provide assistance. Specifically, for rehabilitation applications, they may offer only partial movement assistance, necessitating the user to exert the remaining effort. Secondly, due to their design characteristics (actuation in the frontal plane), it has been demonstrated that they tend to modify the way movement is executed, requiring compensations from the user that may limit the quality of the gesture [**?** ].

For these reason, in this work we proposed a novel state-machine-based control strategy for a lower-limb exoskeleton aiming to provide partial assistance during walking. The control method leverages impedance control, where equilibrium angles are automatically extracted from a benchmark dataset of able-bodied gait across various terrains: level ground, ramps (ascent and descent), and stairs (ascent and descent). The impedance parameters modulate the desired interaction torques between the exoskeleton and the user's leg joints throughout the gait cycle. The state machine dictates transitions between different gait phases (e.g., stance and swing) based on real-time sensor data from the exoskeleton.

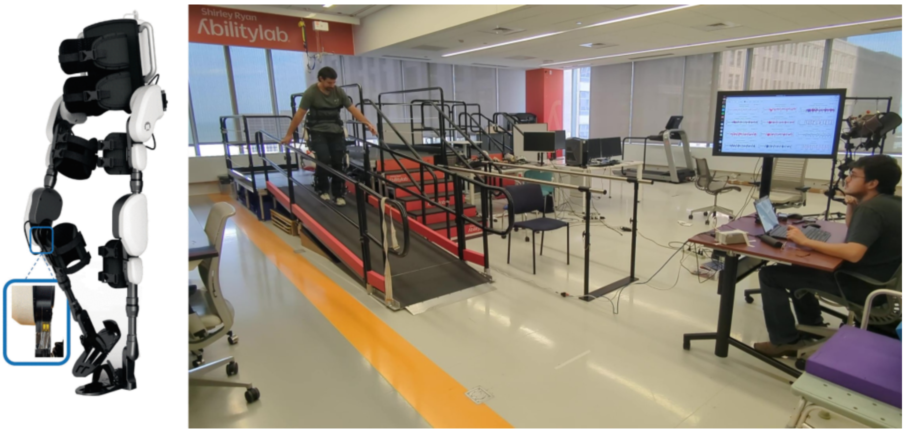


**Fig. 1** X2 Exoskeleton & Example of experimental setup.

# 2 Methods

## 2.1 Exoskeleton Whole Body Controller

A four-degrees-of-freedom (DoF) lower limb exoskeleton (ExoMotus-X2, Fourier Intelligence, Singapore), shown in Figure 1, was adapted and used as a platform to test the proposed state machine controller. This exoskeleton has four total active degrees of freedom at the hip and knee joints, and passively allows motion at the ankle joints. Joint torques are computed using four strain gauges on the limb just distal to the joint. An inertial measurement unit (IMU) (Tech-IMU V4 by Technaid S.L.) is mounted on the backpack to measure the orientation and angular velocity of that link. FSR footplates were installed beneath the soles of the exoskeleton measuring forces between the user-exoskeleton couple and the ground. Each footplate is equipped with 16 force-sensitive resistors, amounting to a total of 32 sensors across both footplates. These sensors interface with the ground through a rigid aluminum sole and rubber bearings, adding a degree of compliance. Communication with motors and onboard sensors is established over a CAN bus using the CANOpen communication protocol [**?** ] based on ROS and C++.

In this work, we used the WECC proposed in our previous work [**?** ]. The exoskeleton is modeled as a floating-base five-link mechanism with four active joints. The dynamics of the human user are modeled into the exoskeleton dynamics as a source of external torque at each joint. The equations of motion of the exoskeleton are described using the classical formulation:

$$M_i(q)\ddot{q} + b_i(q,\dot{q}) + g_i(q) = S^\top \tau_{\text{joint}} + \tau_{\text{int}}, \quad i \in \{\text{ls}, \text{rs}\}, \tag{1}$$

where $q = [\theta_0, \theta_1, \theta_2, \theta_3, \theta_4]^\top$ are the generalized coordinates corresponding to the backpack, hip, and knee angles. The matrix and vectors $M_i \in \mathbb{R}^{5\times5}, b_i \in \mathbb{R}^5, g_i \in \mathbb{R}^5$, are the mass matrix, Coriolis and centrifugal torques, and gravitational torques respectively during left stance ($i = \text{ls}$) and right stance ($i = \text{rs}$). The vector $\tau_{\text{joint}} \in \mathbb{R}^4$ corresponds to joint torques, and $S = [0_{4\times1}, \mathbb{I}_{4\times4}]$ is a selection matrix of actuated joints. The interaction torques applied to the exoskeleton by the user are given by the vector $\tau_{\text{int}} \in \mathbb{R}^5$.

During walking, the exoskeleton alternates this model between two phases of right stance (*rs*) and left stance (*ls*), thereby adapting the mass matrix ($M_{\text{rs}}$, $M_{\text{ls}}$), Coriolis ($b_{\text{rs}}$, $b_{\text{ls}}$), and gravity vector accordingly ($g_{\text{rs}}$, $g_{\text{ls}}$). In the double stance phases, these parameters are interpolated between the two extremes:

$$M_{\text{ds}} = \alpha M_{\text{ls}} + (1-\alpha) M_{\text{rs}}, \tag{2}$$
$$b_{\text{ds}} = \alpha b_{\text{ls}} + (1-\alpha) b_{\text{rs}}, \tag{3}$$
$$g_{\text{ds}} = \alpha g_{\text{ls}} + (1-\alpha) g_{\text{rs}}. \tag{4}$$

where $\alpha$ corresponds to the interpolation factor from left-stance dynamics to right-stance dynamics. The interpolation factor $\alpha$ is calculated based on the ratio of the left vertical ground reaction force to the sum of both vertical ground reaction forces

$$\alpha = \frac{F_{\text{l},y}}{F_{\text{l},y} + F_{\text{r},y}}, \tag{5}$$

where $F_{\text{l},y}$ and $F_{\text{r},y}$ are left and right vertical ground reaction forces, respectively.

## 2.2 State Machine Controller

This framework enables the utilization of a lower-limb exoskeleton in transparent mode ($\tau^*_{\text{int}} = 0$), also providing the capability to explicitly apply interaction torque to individual joints ($\tau^*_{\text{int}} \neq 0$). Impedance control is used to determine the commanded interaction torque of each joint (left or right, hip or knee):

$$\tau^*_{\text{int,i}} = k_{\text{i}}(\theta_i - \theta_i^{\text{eq}}) + b(\dot{\theta}_i - \dot{\theta}_i^{\text{eq}}) \quad i \in \{\text{lh}, \text{lk}, \text{rh}, \text{rk}\} \tag{6}$$

Our state-machine implementation contains a total of 4 different states for each leg. Each stride, for both right and left legs, is divided into 4 states: Early Stance, Late Stance, Early Swing, and Late Swing (Fig. 2). The state machine relies on sensors to switch from the current state to the next one. Transitions across the different states are synchronized between the two legs, and therefore only 6 different combinations of left and right states are possible (Fig. 2).

The stiffness was modulated using the previously introduced weight distribution ($\alpha$). This signal allows us to transition smoothly between two models, one for stance and one for swing (similarly as [**?** ]):

$$\tau^*_{\text{int}} = \alpha \tau^*_{\text{int, stance}} + (1-\alpha)\tau^*_{\text{int, swing}} \tag{7}$$
$$\tau^*_{\text{int, stance}} = k_{\text{stance}}(\theta - \theta^{\text{eq}}) + b_{\text{stance}}(\dot{\theta} - \dot{\theta}^{\text{eq}}) \tag{8}$$
$$\tau^*_{\text{int, swing}} = k_{\text{swing}}(\theta - \theta^{\text{eq}}) + b_{\text{swing}}(\dot{\theta} - \dot{\theta}^{\text{eq}}) \tag{9}$$

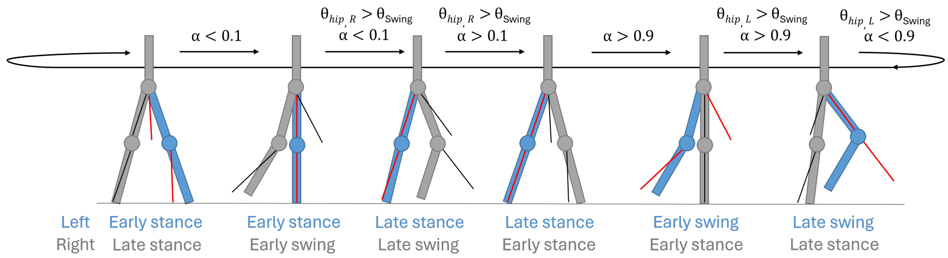


**Fig. 2** State Machine for level-ground walking with different gait states. Sensor value thresholds to switch states are noted at the top of the figure. Examples of desired equilibrium angles are shown in red, corresponding to the positions where the blue leg is attracted (at the hip and knee) via a virtual spring-damper system (Eq. 6). Similarly, examples of equilibrium angles for the right leg (grey) are shown in black.

| Joint | Hip | | | | Knee | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | $k_{\mathrm{st}}$ | $b_{\mathrm{st}}$ | $k_{\mathrm{sw}}$ | $b_{\mathrm{sw}}$ | $k_{\mathrm{st}}$ | $b_{\mathrm{st}}$ | $k_{\mathrm{sw}}$ | $b_{\mathrm{sw}}$ |
| Walking | 90 | 7 | 40 | 3 | 70 | 4 | 30 | 2 |
| Ramps | 80 | 6 | 40 | 3 | 60 | 4 | 30 | 2 |
| Stairs | 60 | 10 | 30 | 5 | 40 | 8 | 20 | 4 |

**Table 1** Starting impedance parameters for the experiment. Stiffness $k$ is expressed in Nm/rad and damping $b$ is expressed in Nm.s/rad.

where $\tau^{*}_{\text{int, stance}}$ and $\tau^{*}_{\text{int, swing}}$ are defined for each joint (left and right, hip and knee), according to Equation 6. This formulation allows us to modulate the provided assistance, according to the ground reaction force of each leg. Therefore, we can provide for example the corresponding joints a stiffer connection to their equilibrium angles in stance phase, in comparison to swing. Parameters associated with both models are presented in Table 1. Different states, transitions and impedance control strategy is referred to as the mid-level control of the X2-exoskeleton.

To navigate among the 5 activities, researchers use a remote connected to the X2-exoskeleton to manually select the activity (walking, ramps up, ramps down, stairs up or down). This layer of hierarchical control is referred to as the high-level control of the exoskeleton.

## 2.3 Extracting equilibrium angles from benchmark dataset

In order to obtain an assistance that produces movements close to reality, the equilibrium angles necessary for the implementation of an impedance control system have been extracted from a database of healthy subjects walking without exoskeletons performing the different tasks (OW, R, ST) [**?** ]. These subjects performed the tasks under different conditions. In particular, we used 28 different speeds during OW, coherent with the walking speed using an exoskeleton; 6 different inclinations have been selected for ramps and finally 4 different step heights for stairs. In this work, we extracted equilibrium angles from this dataset across different task conditions (gait speed, ramp inclination, stairs step height).

To process the data, MATLAB software was used to calculate the equilibrium angles needed to obtain the torque using the impedance control equation.

In this process data from the inverse dynamics calculated from the motion capture data and ground reaction forces using OpenSim software [**?** ] were used.

Our objective is to obtain the equilibrium angles dependent on task conditions (gait speed, ramp inclination, stairs step height) allowing a greater customization for its final use. The original data are grouped in different levels from highest to lowest like subject, task, type of data (IMU, goniometer, markers, inverse dynamics, etc...) and number of trials.

Data belonging to the transitions (stop-walk, up ramps-stop, etc...) have been discarded in this study. Only the complete steps of all subjects have been used for the different tasks so all trials have been divided into the complete steps contained in them using the heel strike information. Step duration has been normalized using the 1D linear data interpolation.

Once all the steps were classified and homogenized, the averages of the hip and knee angles were obtained for each task (OW, ST-A, ST-D, R-A, R-D) and condition (gait speed, ramp inclination, step high). The objective is to obtain hip and knee angle curves that are representative of our population (22 DB subjects). A total of 48 representative curves will be obtained: 28 for walking overground, 12 for ramps (6 uphill and 6 downhill), and 8 for stairs (4 uphill and 4 downhill).

With these curves already calculated we proceed to segment them according to the different phases of the gait. They have been segmented into four phases, two for stance and two for swing. We decided to use a segmentation in four phases to maintain the complexity of movements while allowing a simpler enough number of parameters to be adjusted online to the need of each individual patient. The resulting four phases are: early stance, late stance, early swing, late swing. The division has been performed using the inflection points of the angle curves, namelly the values in which the second order derivative of the curve is equal to zero. Each phase so divided has either a growing trend or a descending one attracting the joint posture to the end point of each phase. This last point has been used in our experiments as the state machine equilibrium angle ($\theta_{eq}$), for each phase.

To fill the missing task conditions and to smooth the transition across them we fit the equilibrium angles using a linear regressor having as domain the task conditions (gait speed, ramp inclination, step height) and as co-domain the hip and knee equilibrium angles. The resulting equilibrium angle can be represented as

$$\begin{aligned}
\theta^{\mathrm{eq}}_{\mathrm{OW,j}} &= A_{\mathrm{OW,j}} * v + B_{\mathrm{OW,j}}, \\
\theta^{\mathrm{eq}}_{\mathrm{RA,j}} &= A_{\mathrm{RA,j}} * s + B_{\mathrm{RA,j}}, \quad \theta^{\mathrm{eq}}_{\mathrm{RD,j}} = A_{\mathrm{RD,j}} * s + B_{\mathrm{RD,j}} \\
\theta^{\mathrm{eq}}_{\mathrm{SA,j}} &= A_{\mathrm{SA,j}} * h + B_{\mathrm{SA,j}}, \quad \theta^{\mathrm{eq}}_{\mathrm{SD,j}} = A_{\mathrm{SD,j}} * h + B_{\mathrm{SD,j}}
\end{aligned}$$

| | Sex | Height | Weight | Age |
|---|---|---|---|---|
| AB68 | M | 1.86m | 90kg | 45y |
| AB69 | M | 1.88m | 70kg | 26y |
| AB70 | F | 1.58m | 51kg | 33y |
| AB71 | F | 1.60m | 55kg | 29y |
| AB72 | M | 1.78m | 81kg | 29y |
| AB73 | F | 1.78m | 70kg | 23y |
| AB75 | F | 1.70m | 56kg | 27y |
| AB76 | M | 1.87m | 80kg | 27y |
| AB77 | F | 1.68m | 81kg | 29y |
| AB78 | M | 1.70m | 70kg | 26y |
| AB79 | M | 1.83m | 84kg | 45y |
| AB80 | M | 1.70m | 73kg | 40y |
| AB81 | F | 1.70m | 62kg | 29y |
| AB82 | M | 1.78m | 73kg | 25y |

**Table 2** Participants

where $A_{\cdot,j}$ and $B_{\cdot,j}$ represent the coefficients that relate each task condition, namely the gait speed ($v$), the ramp slope ($s$) and the step height ($h$), to the equilibrium angle for each gait phase $j \in$ {early-stance, late-stance, early-swing, late-swing}.

## 2.4 Experimental setup and fine-tune parameters

14 healthy subjects (Table 2) participated in this study. The institutional review board of Northwestern University approved this study (STU00212684), and all procedures were in accordance with the Declaration of Helsinky. One participant declared having already walked with an exoskeleton (not ramps or stairs), others declared no previous experience. Users always started in overground walking (OW) to ease the familiarization with the device, Stairs (SA/SD) and Ramps (RA/RD) order was randomized. OW is always the first condition because it permits to familiarize with the exoskeleton, adapting to the constraints imposed by the hardware setup, namely actuation only on the frontal plane. Transparent (TR) or State Machine (SM) conditions were randomly selected to control the exoskeleton. Before each experimental condition (TR and SM) a training time in the specific condition has been provided to each subject. During this training phase, parameters such as walking speed and swing-stiffness level were manually adjusted according to each user's preference, to achieve comfortable walking. The training time varies according to the subject, typically, two iterations for each experimental condition are sufficient to adjust one's strategy to the exoskeleton. Users were instructed to walk at their self-selected speed, for each condition.

Chicago: The experimental setup in Chicago (Fig. 1) is composed of six meters of level-ground walking, a staircase with six stairs of 150mm height, and a 5° ramp (ADA compliant) of 4 meters in length. Users were asked to walk 5 times with each controller (TR & SM), and three times on Stairs (SA/SD) and Ramps (RA/RD).

Spain: The Spanish experimental setup is located inside of the Center for Clinical Neuroscience in Hospital Los Madroños. This facility has a neuro-mechanical laboratory with a setup composed (among other devices) of 13 m of level-ground walking, an active staircase with six steps and variable step height between 110 and 280 mm and 3 m of active ramps with variable inclination between 0 and 15 deg.

## 2.5 Analysis

The first metric presented in this study is the interaction power, as defined in [**?** ]. The Interaction Power is the product of interaction torque and joint velocity, divided by the weight of the user. Negative power shows assistance (i.e. interaction torque in coherence with movement direction), whereas positive interaction power indicates resistance. Main hypothesis tested in this work is that the sum of interaction power (both hips and knees) (per activity?) is greater in transparent control, compared to using the state machine. This shows more resistance with the transparent control.

In particular in this study, we have for each stride i of user j:

$$p_{i,j} = \frac{\sum_{k=0}^{T_i} \dot{\theta}(k)\tau_{int}(k)}{Tw_j} \tag{10}$$

Biological residual torque [**?** ]: interaction torque (or net torque) - inverse dynamic torque

In addition, we incorporated a kinematic analysis section. The first part of this analysis compares non-exoskeleton walking to Transparent and State Machine exoskeleton walking in terms of gait speed, foot clearance (maximum height of the foot during the swing phase), and stride length (distance between two heel strikes of the same foot). For the non-exoskeleton portion, kinematic features were extracted using MediaPipe (Google) pose landmarks detection [**?** ]. Another part of the analysis focuses on hip and knee angles with respect to the gait cycle. The same benchmark dataset used to extract previously defined equilibrium angles [**?** ] is used for this analysis. Notably, we present the average joint angles of users walking on a treadmill at a matching speed of 0.75 m/s (the same speed used to select exoskeleton parameters with the state machine). The average joint angles from the benchmark dataset for ramps and stairs use the same incline (5°) and step height (150 mm) as the exoskeleton experiment. Data were shown using a gait cycle defined from heel strike to heel strike, identified through marker-based methods for the benchmark dataset.

CoM position wrt support region

Prefered Speed

# 3 Results

In this section, we will discuss the performance of the state machine controller, compared to the transparent controller implemented in a previous study [**?** ].

2291 strides kept for analysis!

## 3.1 Parameters extraction

A total of 40 parameters adjusted by least squares were obtained by means of linear regressions. Each of the 5 tasks contemplated in this work contemplates two equilibrium angles (hip and knee) for each of the 4 phases into which a gait cycle has been divided. Fig 3.

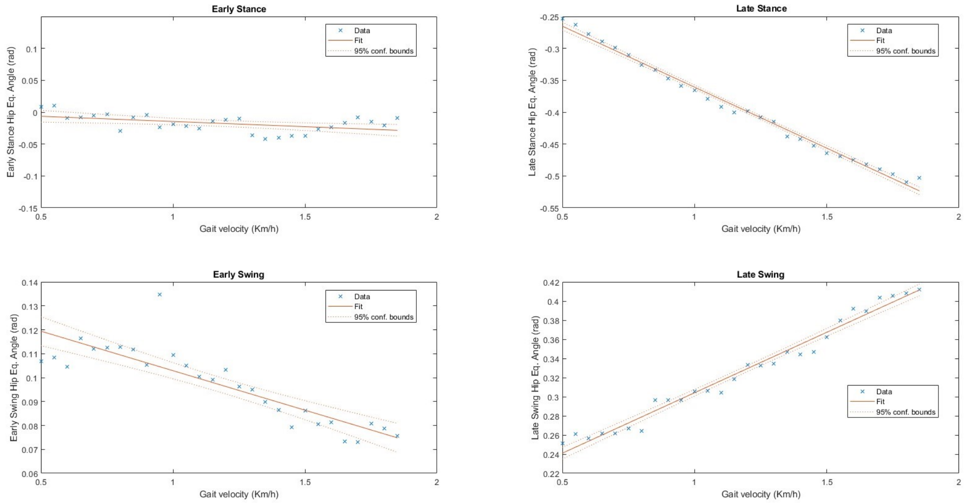


**Fig. 3** Linear adjustment of the equilibrium angles for the hip in the 4 gait phases.

## 3.2 Interaction Power

Figure 4 shows the interaction power for different activities and different controllers. This detailed boxplot allows us to understand that the interaction power seems more negative (i.e. assistive) along different activities using the state machine in comparison to using transparent control. When climbing up stairs, higher assistance seems to be provided at the hip (number..) but not at the knee (number ...). It is also to note that when climbing down stairs, high assistance was delivered at the knee, in comparison to other activities (number..). Linear Mixed Effect model coefficients for net power are statistically different for the two controllers (p-value $< 0.5$) over each activity among 14 users and with the two joints combined (hip and knee).

## 3.3 Biological residual torque

## 3.4 Preferred speed

Figure 5 shows the difference of preferred speed using state machine or transparent control. Most activities present a faster speed using the state machine (on average among 14 users: Walking: 23%, Ramps Up: 25%, Ramps Down: 22% faster). Stairs result in less change (on average 10% faster with the state machine for climbing down, and on average 4% faster in transparent for climbing up).

Also to note higher variance in stairs down (number..).

## 3.5 Kinematics

Explain the change in kinematics using the exo vs not using the exo, Fig 6.

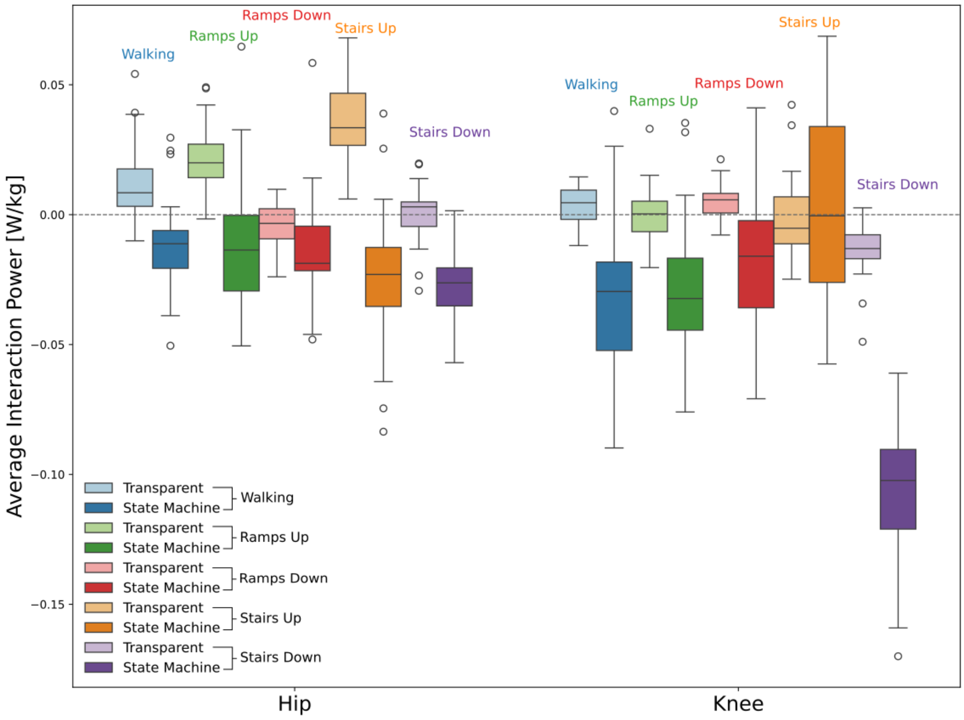


**Fig. 4** Interaction Power for 14 users, each data point represents the average for each user and each activity. Negative interaction power denotes assistance, and positive interaction power shows resistance to user intent. Power is divided by weight to compare among users (todo improve)

Comparison against Camargo: Fig 7. Transparent higher peak in swing among all activities at the hip (walking $R^2$ is 0.77 for State-Machine, 0.51 for Transparent), some users feel they "exaggerate the movement to be able to walk with the exoskeleton". This behavior seems to be attenuated with the state machine. Delay effect observed on the knee, both transparent and state machine (walking $R^2$ is 0.53 for State-Machine, 0.24 for Transparent, todo quantify delay:).

Stairs descent difference is explained by the limited range of motion of the X2-exoskeleton, leading to a strategy taught to the participants to be able to navigate stairs down: exaggerate knee flexion, aiming to land with the middle of the foot at the edge of the stair.

The state-machine successfully modulated the kinematics of the 14 healthy individuals, getting closer to the benchmark dataset than using transparent control only.

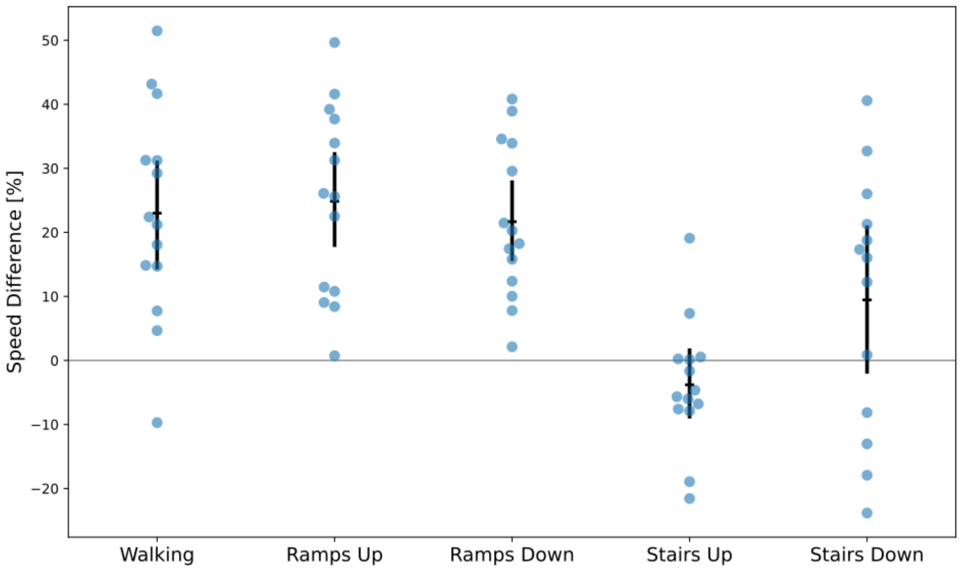


**Fig. 5** Preferred Speed percentage change, between transparent and state-machine conditions, among 14 users. Black Line highlights the average and 95% confidence Interval. Each blue dot represents the average difference speed for a specific user and activity. Positive values show an increase in speed using state-machine condition, compared to transparent control.

# Acknowledgment

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# Appendix A  Section title of first appendix

An appendix contains supplementary information that is not an essential part of the text itself but which may be helpful in providing a more comprehensive understanding of the research problem or it is information that is too cumbersome to be included in the body of the paper.

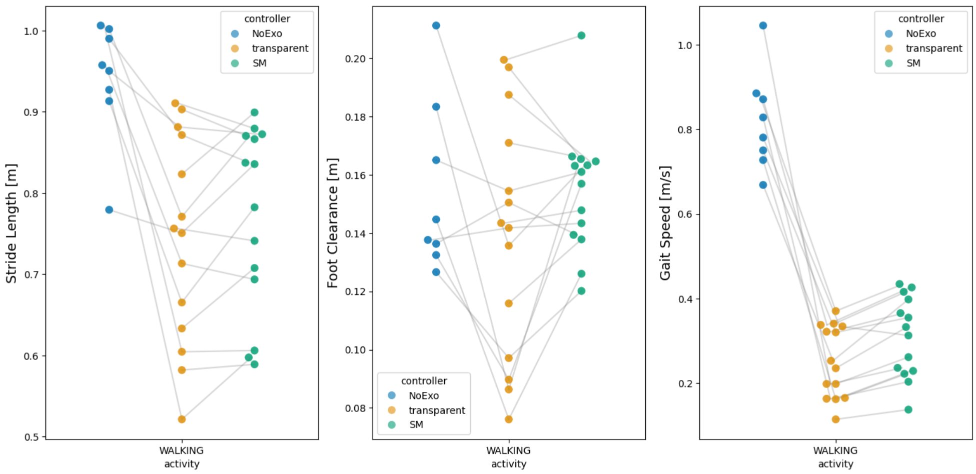


**Fig. 6** Walking stats (no exo compared to exo) – to do improve this. Each dot corresponds to one user average over different strides, grey lines allow us to see variation for a given user across conditions (no exo, transparent, state machine).

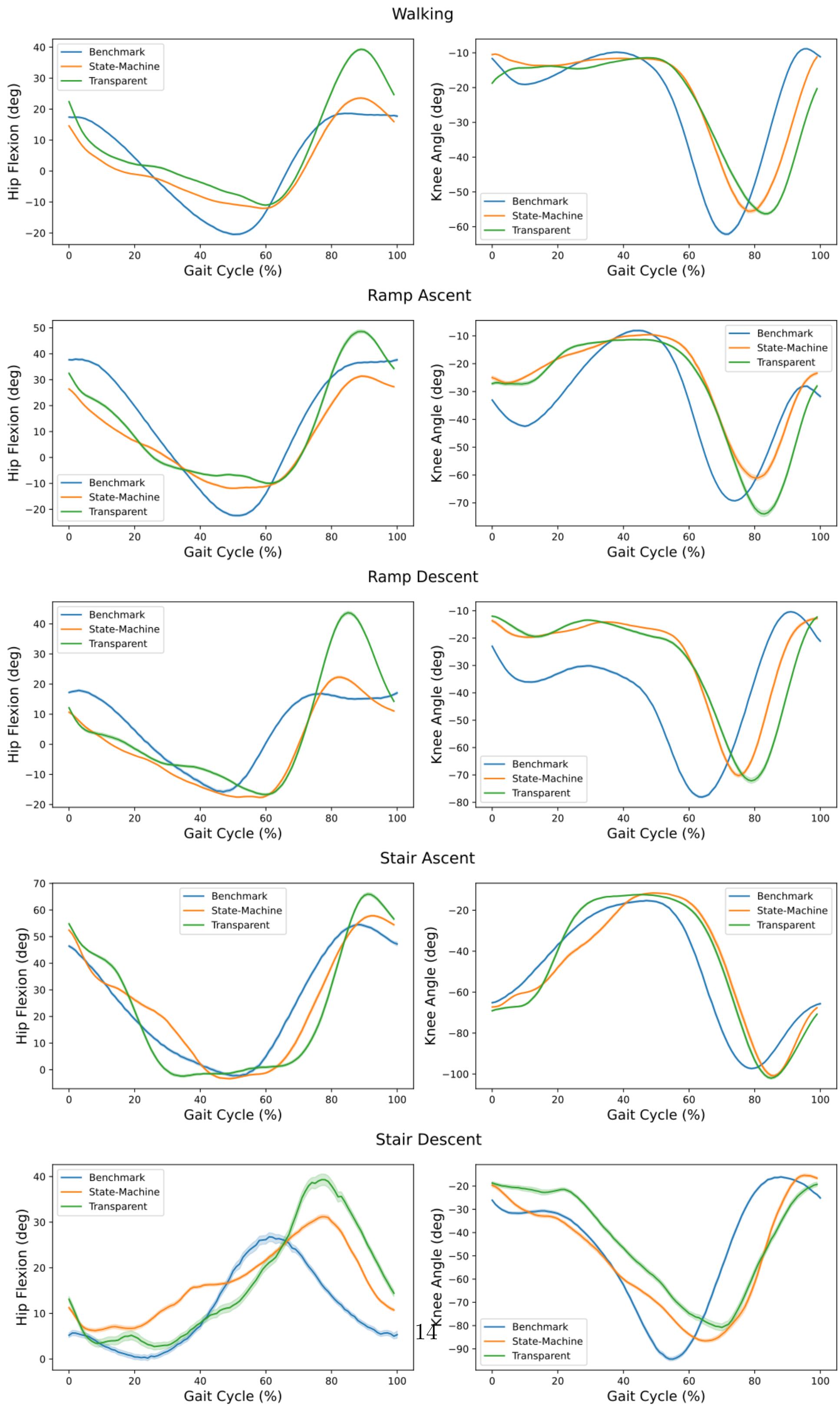


**Fig. 7** Trajectories comparison between transparent, state-machine condition (N=14 users) and benchmark dataset (N=22 users). HS to HS

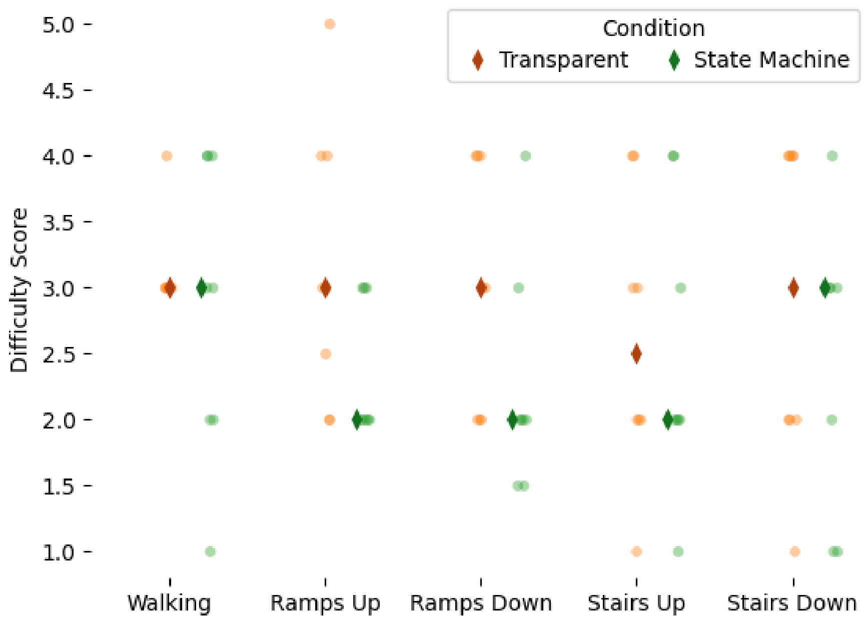


**Fig. 8** Difficulty Score (ranging between 1 and 5) at the end of the experiment. A circular point represents each user and the median across users is highlighted with a diamond. 8 users out of 14 answered fully the questionnaire.