

Enhancement of Human-Robot Physical Interaction in Lowerlimb Exoskeletons

by

Seyed Mohammad Shushtari

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Mechanical and Mechatronics Engineering

Waterloo, Ontario, Canada, 2024

© Seyed Mohammad Shushtari 2024

Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner: José L. Pons, PhD
Professor, Dept. of Physical Medicine and Rehabilitation,
Northwestern University

Supervisor(s): Arash Arami, PhD
Assistant Professor, Dept. of Mechanical and Mechatronics
Engineering, University of Waterloo

Internal Examiner: Soo Jeon, PhD
Associate Professor, Dept. of Mechanical and Mechatronics
Engineering, University of Waterloo

Internal-External Examiner: Ning Jiang, PhD
Professor, Dept. of System Design Engineering, University
of Waterloo

Internal-External Examiner: Katja Mombaur, PhD
Professor, Dept. of System Design Engineering, University
of Waterloo

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Statement of Contributions

The content presented in Chapters 3 to 7 are taken from published or under review research articles listed below:

- Chapter 3
M. Shushtari, H. Dinovitzer, J. Weng and A. Arami, "Ultra-Robust Real-Time Estimation of Gait Phase," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 2793-2801, 2022, doi: 10.1109/TNSRE.2022.3207919.
M. Shushtari, H. Dinovitzer, J. Weng and A. Arami, "Accurate Real-time Phase Estimation for Normal and Asymmetric Gait," *2022 International Conference on Rehabilitation Robotics (ICORR)*, Rotterdam, Netherlands, 2022, pp. 1-6.
- Chapter 4
Shushtari, M.; Arami, A. Human-Exoskeleton Interaction Force Estimation in In-dego Exoskeleton. *Robotics* 2023, 12, 66. doi:10.3390/robotics12030066.
- Chapter 5
Shushtari, M., Foellmer, J., & Arami, A. (2024). Human-Exoskeleton Interaction Portrait. arXiv preprint arXiv:2403.06851, Under review in *Journal of NeuroEngineering and Rehabilitation*.
- Chapter 6
M. Shushtari, R. Nasiri and A. Arami, "Online Reference Trajectory Adaptation: A Personalized Control Strategy for Lower Limb Exoskeletons," in *IEEE Robotics and Automation Letters*, vol. 7, pp. 128-134, Jan. 2022, doi: 10.1109/LRA.2021.3115572.
- Chapter 7
M. Shushtari and A. Arami, "Human-Exoskeleton Disagreement Resolution Through Interaction Torque Minimization: Experimental Results , Submitted to " *2024 International Conference on Biomedical Robotics and Biomechatronics (BioRob)*.

The candidate is the primary author of all manuscripts, and was directly responsible for data collection, result analysis, numerical modeling, and writing of the manuscripts. A number of co-authors have contributed to these research articles. The individual contributions from all of the co-authors are as follows:

- Prof. Arash Arami: Supervised and mentored all the work presented in this thesis.

- Hannah Dinovitzer: Helped with data collection in Chapter 3, also in writing and revision of the manuscript.
- Jiacheng Weng: Helped with training the Temporal Convolutional Neural Network training in Chapter 3, also revision of the manuscript.
- Julia Foellmer: Helped in data collection and result analysis in Chapter 5, also in revision of the manuscript.
- Dr. Rezvan Nasiri: Helped with problem formulation, and simulation design in Chapter 6 as well as writing and revision of the manuscript.
- Livia Murray: Helped in data collection, and result analysis in Chapter 7.

Abstract

Many people face mobility challenges due to spinal cord injury, stroke, and aging. Therapeutic interventions using assistive exoskeletons have emerged as promising tools to enhance their quality of life. The efficacy of exoskeletons requires a delicate balance between assistance and allowing users to regain control of their movements. This needs the exoskeleton to continuously alternate between follower and leader roles to assist the user only when needed. My PhD research focused on proposing a solution for this challenge by optimizing the human-exoskeleton physical interaction. I developed an innovative method to optimize interaction torques, enabling the exoskeleton to adapt its assistance based on the user’s motor capacity. Using musculoskeletal modelling and simulation tools such as OpenSim and MATLAB, I integrated human and exoskeleton models and simulated individuals with varying levels of injuries. I implemented an adaptive approach to determine an efficient exoskeleton trajectory, resulting in improved gait stability and spatiotemporal parameters by decreasing the physical disagreement between the user and the exoskeleton, which is expected to increase the user comfort level. I further extended the optimization formulation to adapt to the changes in gait speed, transitions, and pathological gait patterns by developing a data-driven gait phase estimator using a rich dataset collected from 14 participants, offering superior performance in estimating gait phases under diverse conditions. Moreover, I tackled the issue of measuring interaction torques in practice, where direct measurements are impractical due to the complex nature of human-exoskeleton interaction. I introduced an innovative excitation approach to capture the dynamics of the exoskeleton in all regimes (i.e., swing, stance, and double support) with a single model. This method allows researchers to estimate interaction torques throughout the entire gait phase, ensuring accurate monitoring of the human-exoskeleton interaction dynamics. Leveraging these contributions, I implemented my optimization method in practical settings, and validated its effectiveness in experiments on 15 participants during treadmill and overground walking. Finally, I developed an adaptive feedforward torque controller capable of learning the user desired joint trajectory and accordingly generating an appropriate feedforward torque based on the exoskeleton dynamical model. Comparative assessments on 9 participants against current methods demonstrated that my controller reduces metabolic costs, physical interaction, and enhances the overall user experience compared to a recently developed stated-dependent feedforward controller. As a part of this assessment, I proposed a new method of evaluating human-exoskeleton interaction based on co-analysis of the user muscular effort and the interaction torques called Interaction Portrait. I showed that the distribution of the interaction portrait can determine different regimes of human-exoskeleton physical interaction. In conclusion, the methodologies I introduced contributed to the advancement of assistive robotics. By focusing on optimizing interaction torques, I

addressed a key limitation in contemporary exoskeleton designs, ensuring the device intelligently adapts to the user's unique motor capacities. By successfully addressing real-world challenges, such as adapting to diverse gait patterns and accurately estimating interaction torques, my research offers a tangible and significant improvement in exoskeleton performance. The practical implementation and subsequent evaluations underscore the potential of my approach to not only enhance mobility but also elevate the user experience. My research lays a strong foundation for future endeavours aimed at bridging the gap between robotic assistance and human motor impairments.

Acknowledgments

I would like to thank my supervisor, *Prof. Arash Arami*, who pushed me to achieve my best and supported me throughout my PhD. I learned a lot from you.

Thanks to my family for their unwavering support and sacrifices.

And to my friends in Aramilab, thank you for creating a wonderful and memorable experience for me.

Dedication

Dedicated to ***Sara***, who has made my life colorful.

Table of Contents

Examining Committee Membership	ii
Author’s Declaration	iii
Statement of Contributions	iv
Abstract	vi
Acknowledgments	viii
Dedication	ix
List of Figures	xiv
List of Tables	xxvii
List of Abbreviations	xxviii
1 Introduction	1
2 Literature Review	5
2.1 Intent Detection	5
2.1.1 Intent Definition	5
2.1.2 Relevant Signal Measurement	6

2.1.3	Intent Decoding	9
2.2	Arbitration	12
2.2.1	Conventional Controllers Without Arbitration	13
2.2.2	Passive Arbitration	14
2.2.3	Active Arbitration	17
2.3	Human-Exoskeleton Physical Interaction Evaluation	19
3	Ultra-Robust Real-Time Estimation of Gait Phase	21
3.1	Methods and Material	22
3.1.1	Experimental Setup	22
3.1.2	Experimental Protocol	23
3.1.3	Training and Evaluation of the Gait Phase Estimator	25
3.2	Results and Discussion	28
3.2.1	Detailed Performance Analysis	28
3.2.2	Gait Phase Estimation in Presence of an Exoskeleton	30
3.2.3	Robustness Analysis	32
3.2.4	Comparison with the state of the art	36
3.3	Conclusion	37
4	Human-Exoskeleton Interaction Force Estimation in Indego Exoskeleton	39
4.1	Materials and Methods	39
4.1.1	Interaction Torque Modeling	39
4.1.2	System Identification	40
4.1.3	Experimental Estimation of Human-Exoskeleton Interaction Torque	44
4.2	Results and Discussion	46
4.2.1	Tuning the Network Structure and Hyperparameters	46
4.2.2	N9 Performance on Test Dataset	47
4.2.3	Human-Exoskeleton Interaction Torque Estimation	48

4.3	Conclusions	50
4.4	Supplementary Material: Model-based Estimation of Indego Exoskeleton	51
4.4.1	Indego Exoskeleton	51
4.4.2	System Identification Objectives	52
5	Human-exoskeleton Interaction Portrait	56
5.1	Methods	57
5.1.1	Feedforward Control Strategies	57
5.1.2	Experimental Setup	59
5.1.3	Experimental Protocol	61
5.1.4	Data Analysis	62
5.2	Results	68
5.2.1	Initial Processed Data for a Representative Participant	68
5.2.2	Overall Performance Analysis	68
5.2.3	Interaction Portrait Analysis	69
5.2.4	Individual Adaptation Strategy	71
5.3	Discussion	72
5.3.1	Human Adaptation	72
5.3.2	Importance of Interaction Portrait (IP) Analysis	74
5.4	Conclusion	76
5.5	Supplementary Material: Complementary Example	77
5.6	Supplementary Material: Comparison with Natural Walking	78
5.6.1	Gait Spatiotemporal Parameters	78
5.6.2	Ground Reaction Force	80
6	Online Reference Trajectory Adaptation: A Personalized Control Strategy for Lower Limb Exoskeletons	81
6.1	Problem Statement	82

6.2	Mathematical Analysis	84
6.2.1	Adaptation Rule Extraction	84
6.2.2	Convergence Analysis	85
6.3	Simulator Development	85
6.3.1	Simulator Justification on Healthy Subject Data	86
6.3.2	Simulation of Assisted Walking With an Exoskeleton	87
6.4	Results and Discussion	90
6.5	Conclusion	92
7	Optimization of Human–Exoskeleton Physical Interaction	94
7.1	Methods	95
7.1.1	Interaction force estimation	95
7.1.2	Exoskeleton Controllers	95
7.1.3	Experimental Protocol	97
7.1.4	Data Processing	99
7.2	Results and Discussions	100
7.2.1	Overground Walking	100
7.2.2	Comparison with Treadmill Walking	107
7.2.3	Convergence Behavior	109
7.2.4	Interaction Portrait	110
7.3	Conclusion	111
8	Conclusion and Outlook	112
	References	116

List of Figures

2.1	Physical human-robot interaction framework	6
2.2	Intention detection steps and levels	7
2.3	Control arbitration levels	12
2.4	Spatiotemporal decoupling in Path Control and Velocity Field Control (VFC) method	15
3.1	Experimental setup: a participant walking on the treadmill (A) without and (B) with an exoskeleton. Participants kinematics are recorded using the motion capture and motor encoders during without and with exoskeleton walking, respectively. The ground reaction forces are collected by separate load cells under each belt of the treadmill. The participant has permitted usage of their photo in this paper.	22
3.2	The speed profile during the treadmill walking session. The right and left belts share the same speed profiles except during the asymmetric walking condition.	23
3.3	The TCN network consists of six residual blocks, each including two dilated convolutional layers with the same dilation factor. Instantaneous joint angles ($\mathbf{x}_t$) are fed into the first residual block while the output of the last residual block is fed into a linear layer to generate the final gait phase predictions (ϕ_t). The dropout rate is set to 0.1 for all residual blocks. Kernel size of 3 is used for all dilated causal convolutional layers.	24
3.4	Spatial (e_S) and Temporal (e_T) error according to the estimated and target gait phase profiles. The temporal error (e_T) is computed at the n^{th} heel-strike event.	25

3.5	(A) Spatial Accuracy comparison between the D67, Temporal Convolutional neural Network (TCN), and D5 networks. The circles in each pair of network and condition indicate the mean of spatial Root Mean Square Error (RMSE) across all gait cycles of each participant in all conditions. The average spatial RMSE across the subjects is also represented with the respective bar height. Similarly, (B) compares the temporal MAE of the three networks in treadmill and overground walking conditions. The comparisons denoted by asterisks show significant difference between the average performance of the compared networks. The p -value is smaller than 0.001 unless specified.	26
3.6	The performance of the D67 network in treadmill walking gait phase estimation. (A) the average estimated gait phase profile with respect to the target gait phase. Gait phase estimation standard deviation is shaded in red. (B) the spatial RMSE of the estimated gait phase across the strides in each condition made by all participants. The average RMSE of gait phase estimation at each condition is represented by the respective bar height. (C) the estimated gait phase temporal error across all participants in each condition. The mean and standard deviation of the temporal error are depicted by dashed lines and bold areas, respectively.	29
3.7	The performance of the D67 network in overground walking gait phase estimation. Figure description is the same as Fig. 3.6.	30
3.8	The comparison between the temporal and spatial performance of the D67 network in treadmill walking with the Passive and Active exoskeleton on participant #5. (A) overall average gait phase profiles in Passive and Active modes across experiment conditions. The shaded area shows the standard deviation. (B) the spatial performance across the experiment conditions in the Active and Passive control modes. (C) the temporal error distribution across all conditions in case of the Passive and Active exoskeletons. The mean and standard deviation of temporal errors are denoted by dashed lines and dark shaded area under the curves, respectively.	31
3.9	(A) Comparison of D67, D5, and TCN networks estimated gait phase mean and standard deviation (denoted by shaded area) as the treadmill speed jumped from 0.8 to 1.2m/s averaged across all participants. (B) Detailed performance of the D67 network gait phase estimation in different speed jump scenarios. Each gray line represents one of the subjects while the blue line shows the average gait phase profile.	33

3.10	D67 spatial and temporal performance for each step of the right and left legs during asymmetric walking. The blue and red circles show the performance at each step while the corresponding curve show the smoothed performance. The intervals during which the right and left legs are severely limping are denoted by blue and red shaded areas, respectively	34
3.11	D67 gait phase estimates when the treadmill belts have stopped and start moving again for participant #5 without exoskeleton and with the exoskeleton in the Passive and Active mode, respectively. The shaded area shows the interval when the treadmill belts were fully stopped.	35
3.12	Comparison of D67 gait phase estimator performance with approaches reported in the literature for (A) fixed speed, (B) speed jumps, and (C) speed sweep in treadmill walking as well as overground walking at (D) preferred speed and (E) variable speeds.	36
4.1	(A) The exoskeleton coordinates and joint angles. The global, trunk, and thigh frames are denoted by 0, 1, and 2 indices, respectively. The trunk and thigh angles with respect to gravity vector are denoted by θ and γ , respectively. q_h and q_k represent the hip and knee joint angles, respectively. $\mathbf{p}_1$ and $\mathbf{p}_2$ shows the position of the trunk and thigh coordinated in the global frame $((x_0, y_0))$. In blue, the acceleration vector ($\mathbf{a}$) measured by the accelerometer embedded in the exoskeleton's thigh is plotted against the thigh frame. In red, we plotted the interaction force vector ($\mathbf{f}_{int}$) calculated from the linear spring's deflection measured by motion capture. The distance from the trunk frame origin to the hip joint rotation axis and from there to the accelerometer location on the exoskeleton's thigh is indicated by l_1 and l_2 , and the gravity axis is illustrated by dashed lines. (B) The exoskeleton in hung position during data collection for dynamics identification. Joints are excited during the experiment while the exoskeleton interaction with the environment is limited to the force applied through a linear spring with reflective markers on both ends enabling us to measure the spring deflection using a motion capture system and, consequently, the applied force.	41
4.2	The hip and knee excitation torques applied to the left and right exoskeleton legs, as well as the interaction force on the y axis. During the generation of each of the training, validation, and test datasets, exoskeleton joints were activated with unique and different chirp commands resulting in different exoskeleton–environment interaction profiles.	43

4.3	(A) Block diagram of the exoskeleton dynamic identification experiment. The interaction force (f_{int}) is applied to the exoskeleton through a linear spring through which the exoskeleton is hung. Exoskeleton joints are controlled by chirp position commands using PD controllers applying the excitation torques (τ_{act}) to the exoskeleton. Measurements of the exoskeleton (x), containing joint angles and their derivatives as well as the thigh angle with respect to the gravity vector and its linear acceleration, are fed to a neural network for the estimation of the interaction force ($\hat{f}_{\text{int}}$) and motor torques ($\hat{\tau}_{\text{act}}$), which are then compared to their actual values. The estimation error is then used to update the neural network weights to improve its estimation accuracy. (B) Structure of a time-delay neural network with 10 input delays and 3 hidden layers with 50, 50, and 20 neurons, respectively, with a <i>tanh</i> activation function.	45
4.4	(A) Validation performance of ANNs with 10 different structures in terms of RMSE and adjusted R^2 computed on the z-normalized data. The training procedure was repeated 5 times for each structure to study the sensitivity of the training procedure to the network's initial weight for each structure. Each validation performance is denoted by a black dot while the average performance is denoted by bars. The training was conducted with 5 input delays and no regularization. N3 (denoted by red) and N9 (denoted by blue) demonstrated a better performance compared to the other networks. N9, however, exhibited more variability across training repetitions. Those networks were selected for further analysis to investigate the effect of regularization factor and the number of input delays. (B) Comparison of N3 and N9 performance across different selections of regularization factors. The variation of the N9 performance across training repetitions is unaffected by regularization. (C) Effect of the number of input delays on the N3 and N9 networks' performance. N3 has the best performance with 5 input delays while N9 reaches the best performance at 10 input delays.	46

4.5	The test performance of N9 for each output channel. In the top row, the distribution of the estimation error of external force or joint applied torques relative to their peak-to-peak range is depicted. Interaction forces in the y and x direction exhibit a higher estimation error compared to those of the exoskeleton active joints. Applied torques to the hip joints, in particular, are estimated with a higher accuracy and smaller standard deviation. Even though knee joint applied torques are estimated with similarly small errors (small bias), they show a higher standard deviation associated to the more prominent role of static friction. The bottom row shows the correlation between the measured data and the N9 estimation for each output channel. The estimated outputs have a relatively lower coefficient of determination in case of interaction forces, while they show $R^2 > 0.9$ for the active joints of the exoskeleton.	49
4.6	The estimated interaction torques at (A) the hip and (B) the knee joints of the right leg for three participants walking at different speeds (ranging from 0.4 m/s to 0.8 m/s) are shown. The values represent the average across different steps. The solid lines represent the median of the estimated interaction torque, while the shaded area represents the torques that fall within the 5th to 95th percentile. Positive torque values are in favor of joint flexion while negative values are in favor of joint extension.	50
4.7	Indego exoskeleton and modeling of swing leg by a two-link manipulator .	52
4.8	Single joint identification of hip and knee joints	53

5.1	Block diagram of Time-Based Control (TBC), Hybrid Torque Control (HTC), and Adaptive Model-based Torque Control (AMTC) controllers. (A) Block diagram of the Time-Based Controller (TBC). A time-based gait phase along with the estimated gait speed are fed into a lookup table to determine the applied torque to the exoskeleton joints according to joint torque data recorded from the exoskeleton during high-gain joint control with the user passively following the exoskeleton (with the minimum voluntary contribution to the gait). (B) The diagram of the Hybrid Torque Controller (HTC) consisted of a data-driven required joint torque estimator along with a look-up table-based torque controller similar to the TBC. In this case, however, the gait phase is determined according to the exoskeleton states rather than time. The torque from the two different pipelines is finally combined with the weight of w and $1 - w$ to form the applied torque to the exoskeleton. (C) Block diagram of the Model-Based Torque Controller (AMTC). The gait phase is estimated according to the exoskeleton joint angles and then fed into a trajectory adaptation block which learns the joint trajectory of the participant in real time and uses that trajectory as the reference for the exoskeleton to be fed into the forward dynamics of the exoskeleton to determine the feedforward joint torques.	57
5.2	Dorsal, lateral, and frontal view of a participant with the Indego exoskeleton with active hip and knee joints. The participant is standing on the Bertec treadmill with two speed-controlled belts equipped with individual loadcells underneath each of them for Ground Reaction Force (GRF) monitoring. Muscle activation is measured from both right and left leg muscles using ElectroMyoGraphy (EMG) sensors. Gait up IMUs are clipped to the outer side of the shoes right bellow ankle joints to measure the spatiotemporal parameters of gait. Oxygen uptake of the participant is measured and recorder at each breath through a mask connected to the gas analyzer device carried at the back of the participant.	60
5.3	Treadmill speed changes while experimenting with the HTC, AMTC, and the TBC controller. The order of the controllers was specific to participant #1 and varied for other participants. Participants walked with each controller for 300 seconds divided by three 100-second walking periods during each the treadmill speed was set to ultra-slow (0.4 m/s), slow (0.6 m/s), and moderate (0.8 m/s) speeds.	61

5.4	Regions of Interaction Portrait (IP). Each quadrant of the circle corresponds to different human-exoskeleton interaction modes determined by the variation of the normalized total muscle activation (${}_{c_1}^{c_2}\Delta\mu$) with respect to the normalized total interaction torque (${}_{c_1}^{c_2}\Delta\tau$) between controllers c_1 and c_2 , respectively. The first quadrant (red) indicates increased disagreement between the user and exoskeleton, resulting in an increase in both muscle effort and the total interaction torque. The second quadrant (green) determines the co-adaptation of the user toward participating in the motion as much as possible and leading the motion. The third quadrant (blue) denotes the decrease in total interaction torque and the total muscle effort, associated with the decrease in human-exoskeleton disagreement. Finally, the fourth quadrant (orange) denotes the condition at which the user yields control of the motion to the exoskeleton and minimally activates their muscles. In this case, muscle activation decreases while the total interaction increases since the exoskeleton has to carry the user's body (passive dynamics) in addition to the exoskeleton dynamics.	65
5.5	A portion of a typical participant's experimental data; for ease of visualization and interpretation, the interaction torque at the right hip and activation of one of the muscles are illustrated along with the relative oxygen uptake. (A) The mean absolute interaction torque at the right hip at each stride with each controller and speed for Participant #1. (B) Normal muscle activation for the Gastrocnemius Medialis at the right leg. (C) Relative oxygen uptake for each breath for each controller and speed. The oxygen uptake has increased with the increase in treadmill speed.	67
5.6	The average performance metrics for each treadmill speed and controller across participants. (A) The sum of the relative oxygen uptake across all the strides for each speed in each controller block graphed for each participant. The bars show the average of the sum of the oxygen uptake across all participants. Similarly, the average total absolute value of the human-exoskeleton interaction and total normalized muscle effort are graphed in (B) and (C) , respectively.	69

5.7	Comparing the Average Interaction Portrait for each Pair of Controllers. The average Interaction Portrait (IP) depicted according to the average total muscle effort and the average total human-exoskeleton interaction for each participant computed at each of the ultra-slow, slow, and moderate-speed walking for the TBC→HTC, TBC→AMTC, and HTC→AMTC illustrated in (A) , (B) , and (C) , respectively. The yellow areas denote the area between the 25 and 75 percentiles.	70
5.8	Comparison of the Interaction Portrait distribution between TBC→HTC and TBC→MTBC. Interaction portrait distribution for HTC and AMTC blocks with respect to the average total muscle effort and total interaction torque across all strides during the TBC block graphed for each participant plotted for moderate speed walking. The radius of data points is normalized with respect to the maximum radius computed across all participants' strides. Participants are arranged increasingly according to their body mass. The polar histograms show the concentration intensity of the depicted points. Each bin of the histogram covers $\pi/6$ rad.	71
5.9	Muscle activation and interaction torque profile with respect to the gait phase. (A) The average normalized muscle activation pattern for the TBC, HTC, and MBTC blocks for the right Gastrocnemius Medialis during ultra-slow, slow, and moderate-speed walking. The shaded area represents the standard deviation of the muscle activation about their mean value. Similarly, the average human-exoskeleton interaction torque at the right hip is plotted in (B)	73
5.10	Evolution of IP phase at each stride at different walking speeds for two sample participants. The top and bottom rows depict IP phase evolution at ultra-slow, slow, and moderate speed walking for each of the TBC→HTC and TBC→AMTC cases for participants #3 and #6, respectively.	74

5.11	(A) Evolution of the modification term for Participant #1's right hip trajectory (Δ_{hip}). Δ_{hip} is zero before and after the AMTC block. During the AMTC block, the modification term of the trajectory adapts to make the reference trajectory closer to the user joint angle. At each of the ultra-slow, slow, and moderate walking speeds, the modification pattern in the steady state converges to a different amplitude and shape, indicating that the user joint angle, and as a result, the exoskeleton reference trajectory has evolved to a different pattern at each speed. (B) Modification trajectory coefficients evolve during the AMTC block. Each coefficient has converged to a steady state value at the end of each treadmill speed condition. After the change in treadmill speed, coefficients converge to new optimum levels. These levels, as mentioned for the modification term of the hip trajectory, differ for each speed. (C) Pearson correlation between the GRF of each stride with the average GRF profile recorded during natural walking without the exoskeleton. (D) Stride length computed using the Physiolog 6s Inertial Measurement Unit (IMU) sensors.	77
5.12	The average maximum heel clearance (A), minimum toe clearance (B), stance percentage (C), and stride length (D), computed for each of the ultra-slow, slow, and moderate speeds during natural walking with no exoskeleton, TBC, HTC, and the AMTC blocks for each participant. Bars show the average of each metric across participants.	79
5.13	(A) The average Pearson correlation computed between the average vertical GRF in natural walking without the exoskeleton and the vertical GRF during walking with each of the proposed controllers at different speeds. Depicted bars show the average of each metric across participants. (B) and (C) shows the similar graph for the lateral and longitudinal GRF plotted only during the moderate speed.	80
6.1	Human and exoskeleton dynamical interaction block diagram. The exoskeleton reference trajectory ($\mathbf{r}(t)$) is adapted based on the feedback from interaction force ($\mathbf{F}$). Human and exoskeleton controllers try to minimize their tracking error.	82

6.2	Dynamic walking simulator block diagram. The human and exoskeleton controllers are implemented in MATLAB interfacing with the human and exoskeleton models defined in OpenSim along with ground reaction forces. The human tries to control her joint positions ($\mathbf{q}$) on her intended trajectory ($\mathbf{p}$) while the exoskeleton, with no information about the human intended trajectory, tries to minimize the error between the exoskeleton position ($\mathbf{q}$) and reference trajectory ($\mathbf{r}$). The saturation is added to the human control loop to simulate reduced motor capacity.	83
6.3	The comparison of the simulator and experimental data of a healthy subject (provided in [117]); the gray background indicates the stance phase. The position of the simulator joints closely follows the experimental human trajectory. The torque profiles' sign and order of magnitude are also close to the ones of human torque profile such that the R -values for hip, knee, and ankle torques are 88%, 45%, and 76%, respectively. In addition, timing and order of magnitude for ground reaction forces are acceptable, and R -values for GRF in y and x directions are 96% and 85%, respectively.	87
6.4	Exoskeleton reference trajectory adaptation at the hip, knee, and ankle joints (simulation results). The gray background indicates the stance phase. Each plot includes the human intended trajectory (in red), which is not known by the exoskeleton controller, initial exoskeleton trajectory (in green), and adapted exoskeleton trajectory (dashed lines). Subject B, C, and D are simulated with different reductions in motor capacity to generate the necessary joint torques for predefined intended motion according to Tab. 6.3. . . .	88
6.5	The adaptation performance (started at $t = 10s$) comparison in four different subjects. The first row presents the normalized moving average (the window length is $T = 1.23s$) of the trajectory modification and interaction force terms in cost function. The second row illustrates the moving average of the exoskeleton absolute tracking error. Final row is the variations of the modification trajectories in course of adaptation.	89
6.6	Comparison of the joint angles and the interaction torques of the simulated subjects before (dashed lines) and after (solid lines) the adaptation.	91
6.7	Adaptation effect on gait stability (left), step time asymmetry index (middle), and minimum toe clearance (right) across subjects. The gray area denotes the adaptation process started at $t = 10s$ (step #8). Green markers indicate the simulated healthy subject metrics without exoskeleton.	91

7.1	(A) Block diagram of gait phase-based controller (referred to as non-adaptive controller). Exoskeleton desired trajectories (r_0) are generated as a function of the gait phase using a lookup table obtained during passive walking at slow speed. The gait phase is estimated in real-time using a pre-trained neural network [122]. (B) Exoskeleton controller with adaptive trajectory (referred to as adaptive controller). Human-exoskeleton interaction torques are estimated using a pre-trained time-delay neural network according to the exoskeleton measurements ($\mathbf{x}$) [123]. The Fourier coefficients ($\boldsymbol{\theta}$) are then adapted, accordingly, and multiplied by the time-based basis functions containing the first three harmonics of the Fourier series generating the trajectory modification term (Δ). Finally, the exoskeleton desired trajectory r is obtained by the addition of the initial trajectory (r_0) and Δ	96
7.2	Treadmill speed variations during treadmill walking are presented. The experiment begins with 105 strides of walking with a passive exoskeleton, equally distributed among slow (0.6 m/s), ultra-slow (0.4 m/s), and moderate (0.8 m/s) speeds. The passive exoskeleton's trajectory is learned as a function of the gait phase at the slow speed and is used as the initial trajectory (r_0) for subsequent control phases. Following this, a gait phase-based control without trajectory adaptation (non-adaptive) is tested for a similar duration as the passive walking phase. Trajectory adaptation is then activated during slow walking, a condition that persists for 105 strides. Afterward, the treadmill speed is adjusted to moderate and ultra-slow speeds, each maintained for 52 strides, respectively. The adaptive controller is tested over a longer duration than both the non-adaptive and passive scenarios to ensure convergence.	98
7.3	(A) A typical participant walking on the treadmill with the exoskeleton while ground reaction forces are measured using force plates under the treadmill belts. Foot kinematics are recorded using Inertial Measurement Units (IMUs) (Physilog 6s, Gait Up SA, CH) attached to the top of both shoes and spatiotemporal parameters are estimated using a Gait Analysis package (GaitUp SA, CH) [67]. Kinematic and muscle activation data are also collected using EMG sensors at 2KHz and the exoskeleton IMUs and encoders at 200 Hz. (B) Another participant during overground walking, the same experimental setup except the instrumented treadmill.	99

7.4	(A), (B) , and (C) show the distribution of the average Mean Absolute Interaction Torque (MAIT), Mean Absolute Tracking Error (MATE), and Mean Absolute Exoskeleton Torque (MAET) for the hip and knee joints with non-adaptive and adaptive controllers across participants during overground walking, respectively. (D) shows the muscular effort computed for the measured muscles at the right leg for each controller relative to those of walking with passive exoskeleton. Similarly, (E) illustrates the spatiotemporal gait metrics. Values in (A) and (D) are normalized by the metrics computed during walking with passive exoskeletons as baseline. Values in (E) are normalized over natural walking with no exoskeleton as a baseline. The gray, red, blue, and black asterisks denote significant differences identified in passive-to-baseline, adaptive-to-baseline, and between-controller comparisons, respectively. Squares denote the population mean and crosses indicate the outliers.	101
7.5	Joint angles, interaction torques, tracking error, motor torques, and normalized muscle activation illustrated in (A), (B), (C), (D), and (E), respectively, averaged across participants and strides within each controller and temporally normalized based on gate phase. The shaded area denotes the interquartile range. The gray area also indicates the stance phase.	104
7.6	Evolution of the muscular effort (A), gait spatiotemporal metrics (B), MAIT (C), MATE (D), and MAET (E) illustrated for each stride. The black and yellow lines show the mean and median of each metric across participants at each stride. The shaded area represents the interquartile range. Metrics are normalized to their average value during walking with passive exoskeleton except for the motor applied torque which is normalized to its average value during with the non-adaptive controller.	106
7.7	The change of MAIT, MATE, MAET, and muscular effort with the adaptive controller relative to the non-adaptive control during treadmill walking at ultra-slow (0.4 m/s), slow (0.6 m/s), moderate (0.8 m/s), and overground walking (at proffered speed) are depicted in (A), (B), (C), and (D), respectively.	108
7.8	Adaptation of the modification trajectories at the hip (A) and the knee (B) joints illustrated for a sample participant during treadmill walking at ultra-slow, slow, and moderate speeds. Similarly, (C) and (D) show the convergence patterns of the Fourier coefficients of each joint.	109

- 7.9 Interaction portrait depicted for the non-adaptive and adaptive controllers compared to passive walking with the exoskeleton as a baseline at ultra-slow, slow, and moderate speed walking on the treadmill as well as overground walking with preferred speed. Each point represents one of the participants. 110

List of Tables

1.1	Identified gaps and my PhD research contribution in addressing each of them.	3
3.1	Comparison of D67, TCN, and D5 network Performances.	28
4.1	Upper leg and hip joint identification with and without consideration of static friction effect.	55
4.2	Lower leg and knee joint identification with and without consideration of static friction effect.	55
6.1	Exoskeleton and healthy human controller parameters.	86
6.2	Simulated joint torques R-value compared to other works.	87
6.3	Relative controller parameters of impaired subjects compared to healthy subject (Tab. 6.1).	88

List of Abbreviations

AAN Assist As Needed [1](#), [13](#), [14](#), [18](#)

AMTC Adaptive Model-based Torque Control [xix](#), [xxi](#), [xxii](#), [56–59](#), [61](#), [62](#), [66](#), [68–72](#), [74–80](#)

ANN Artificial Neural Network [16](#), [44](#), [113](#)

AO Adaptive Oscillator [16](#), [36](#), [37](#)

BF Biceps Femoris [62](#), [99](#), [102](#), [103](#), [105](#)

BMI Brain Machine Interface [6](#)

CNN Convolutional Neural Network [17](#), [37](#)

CNS Central Nervous System [5](#)

ECoG ElectroCorticoGraphy [6](#), [7](#)

EEG ElectroEncephaloGraphy [6](#), [7](#)

EMG ElectroMyoGraphy [xix](#), [xxiv](#), [6–9](#), [60](#), [62](#), [97](#), [99](#)

FES Functional Electrical Stimulation [1](#)

FMG Force MyoGraphy [7](#), [8](#)

FVA Foot Velocity Algorithm [25](#)

GM Gluteus Maximus [62](#), [68](#), [72](#), [99](#), [102](#), [105](#)

GP-EKF Gaussian Process extended Kalman filter 36, 37

GRF Ground Reaction Force xix, xxii, xxiii, 22, 25, 59, 60, 62, 77, 78, 80, 86, 87

HTC Hybrid Torque Control xix, xxi, xxii, 56–58, 61, 62, 66, 68–80

IMU Inertial Measurement Unit xxii, 16, 51, 77

IP Interaction Portrait xii, xx, xxi, 3, 4, 56, 64, 65, 69–72, 74–76, 110, 112, 114

iSCI incomplete Spinal Cord Injury 1, 13, 18, 83, 87, 93

KF Kalman Filter 16

LFP Local Field Potential 6

LQR Linear Quadratic Regulator 18

LSTM Long Short Term Memory neural network 16

MAE Mean Absolute Error 27

MAET Mean Absolute Exoskeleton Torque xxv, 100, 101, 106, 108

MAIT Mean Absolute Interaction Torque xxv, 100–102, 106–108

MATE Mean Absolute Tracking Error xxv, 100, 101, 106–108

MG Medialis Gastrocnemius 62, 99, 102, 105

minTC Minimum Toe Clearance 84, 92

MSE Mean Square Error 25, 55

MVC Maximum Voluntary Contraction 62

NARX Nonlinear Autoregressive network with eXogenous inputs 11

pHRI physical Human-Robot Interaction 5, 10, 12

PNS Peripheral Nervous System 5

RF Rectus Femoris [62](#), [99](#), [102](#), [103](#), [105](#)

RMSE Root Mean Square Error [xv](#), [21](#), [26–29](#), [33](#), [37](#), [38](#)

SCI Spinal Cord Injury [1](#), [115](#)

Sol Soleus [63](#), [99](#), [102](#), [105](#)

STAI Step Time Asymmetry Index [84](#), [92](#)

TA Tibialis Anterior [63](#), [99](#), [102](#), [105](#)

TBC Time-Based Control [xix](#), [xxi](#), [xxii](#), [56–58](#), [61](#), [62](#), [66](#), [68–75](#), [77–80](#)

TBE Time-Based gait phase Estimator [36](#), [37](#)

TCN Temporal Convolutional neural Network [xv](#), [xxvii](#), [26–28](#), [32](#), [33](#)

VFC Velocity Field Control [xiv](#), [15](#), [17](#)

VM Vastus Medialis [62](#), [99](#), [102](#), [105](#)

ZMP Zero Moment Point [84](#)

Chapter 1

Introduction

Every year, between 250,000 and 500,000 individuals worldwide suffer from Spinal Cord Injury ([Spinal Cord Injury \(SCI\)](#)) [99]. A significant portion of these individuals, especially those with incomplete Spinal Cord Injuries ([incomplete Spinal Cord Injury \(iSCI\)](#)) and an ASIA score of C or D, can regain their ability to walk [108, 115]. Consequently, various assistive devices and techniques have been developed to aid their recovery. Noteworthy among these are physical therapy, neuroprosthetics, pharmacological stimulation, functional electrical stimulation ([Functional Electrical Stimulation \(FES\)](#)), and rehabilitation exoskeletons [7, 9, 16, 27, 43, 53, 79].

In particular, assistive exoskeletons have made rehabilitation more accessible and efficient, allowing individuals with [iSCI](#) to engage in frequent training sessions that can enhance their neuromotor control recovery [22]. Additionally, these devices hold significant potential for improving the daily experiences of individuals, enhancing their mental condition, and preventing muscle atrophy in the long term [90]. These benefits have motivated several studies to introduce novel control strategies for exoskeletons, ranging from force control [8] and trajectory control [31] to purely reflex-based controllers [28, 150].

Early exoskeleton controllers were designed to dictate motion to users, regardless of their intentions, a method shown to be counterproductive for post-stroke patients and individuals with [iSCI](#) [49, 110]. Therefore, recent developments in the field have shifted towards controllers that provide minimal support for gait execution, encouraging patients to maximize their capabilities. These controllers, known as Assist As Needed ([Assist As Needed \(AAN\)](#)) controllers, have been suggested to accelerate rehabilitation more efficiently by engaging and stimulating the neuromuscular system more effectively [108]. Such a controller is required to accurately synchronize with the user's desired motion, identify

excessive physical disagreement and react with agility. Even though several methods have been proposed to address each of these requirements, a resilient and robust framework for addressing these needs with the minimum instrumentation and complexity is still a shortcoming.

The dependency between the temporal and spatial guidance is one of the main shortcomings of the conventional control approach such as impedance control. Spatiotemporal decoupling of exoskeleton assistance is, therefore, a critical aspect of advanced controllers, allowing users to modify their gait speed and pattern independently without losing the assistance provided by the exoskeleton. Consequently, the desired behaviour of the exoskeleton is defined not based on time but on internal states such as gait phase [27] or joint coordination phase [95]. This approach addresses the synchronization problem of exoskeleton assistance with the user’s desired motion, as the temporal evolution of such variables is inherently in harmony with user movement. Achieving successful spatiotemporal assistance decoupling, however, requires robust and agile estimation of the gait phase. To this end, I designed and trained a real-time robust gait phase estimator aimed at accurately and robustly estimating the gait phase for an unseen participant under all aforementioned conditions, serving as the backbone of the subsequently developed controller during my PhD.

In addition to spatiotemporal decoupling, estimating and optimizing the physical interaction between humans and exoskeletons plays a pivotal role in enhancing the performance of assistive exoskeletons [53, 61, 78].

Estimating the physical interaction between humans and lower body exoskeletons requires prior identification of exoskeleton dynamics. This process is typically simplified by conditioning it to the gait cycle (stance/swing) or constrained conditions such as fixed trunk sections. By proposing a new method for data collection, I identified and validated the dynamics of the Indego exoskeleton unconstrained and during physical interaction with the environment. This allowed me to estimate the physical interaction between humans and the exoskeleton throughout the entire gait phase.

Controlling the physical interaction between humans and assistive exoskeletons is crucial to ensure the appropriate amount of support is delivered to the user without imposing unnecessary physical discomfort or encouraging complete reliance on the assistance. To achieve this, I developed an online trajectory adaptation method for optimizing physical interaction in lower body exoskeletons, validated through a simulator developed separately using Matlab and Opensim. A more advanced version of this method, encompassing gait phase estimation and interaction estimation, was then tested to demonstrate the effectiveness of the developed method in practice. Besides the feedback controllers, which play a

corrective role, feedforward controllers are also essential for agile assistance. To fulfill this requirement, I adapted the developed technique to learn the user’s trajectory and utilized the identified dynamics of the exoskeleton to generate adaptive feedforward torques based on the gait phase. Furthermore, to compare the performance of different controllers, I introduced the Interaction Portrait (IP) analysis. Unlike conventional methods that separately examine physical interaction or muscular effort, IP co-analyzes these metrics. This approach allows for the determination of whether the tested controller encourages the user to yield to the controller’s motion or to lead it. It also assesses the extent to which each

Needs	My PhD contribution
A reliable gait phase estimator	Developing a robust real-time gait phase estimator that maintains its accuracy for a new participant during wide ranges of gait speed, transitions and abnormal walking.
Human-exoskeleton physical interaction estimation	Identifying the dynamics of the Indego exoskeleton regardless of gait phase and estimating the human-exoskeleton interaction torques accordingly.
An agile adaptive feedforward (assistive) strategy	Developing an adaptive feedforward controller that modifies exoskeleton assistance according to gait phase and user trajectory.
A metric for comparing controllers with respect to physical interaction	Proposing the Interaction Portrait (IP), allowing co-analysis of interaction torque and muscular effort to distinguish between different human-exoskeleton interaction modes.
A simulation framework for exoskeleton controller simulation in interaction with human musculoskeletal model	Developing a simulation environment for the design and testing of exoskeleton controllers using Matlab and Opensim.
Personalizing Path and flow control with respect to physical interaction	Proposing, validating, and experimenting a real-time trajectory adaptation method for optimizing human-exoskeleton interaction torques with adjustable adaptation capacity to accommodate a range of user impairments.

Table 1.1: Identified gaps and my PhD research contribution in addressing each of them.

controller is successful in rectifying excessive physical disagreements between the human and the exoskeleton. Identified gaps and my PhD research contributions addressing each of them are summarized in [Tab. 1.1](#).

My thesis is structured as follows: Chapter 2 presents a review of existing control methods for lower limb exoskeletons. Chapter 3 introduces a robust gait phase estimator. Chapter 4 discusses the method used for identifying Indego dynamics and estimating human-exoskeleton interaction torques. Chapter 5 introduces the Interaction Portrait analysis and an adaptive feedforward controller. Chapter 6 presents an online method for optimizing human-exoskeleton interaction torque, validated through simulation with participants with varying levels of motor impairment. Chapter 7 integrates the works from previous chapters, proposing a real-time interaction torque optimizer based on gait phase and interaction torque estimation, experimented and analyzed using [IP](#) analysis. Finally, Chapter 8 concludes my PhD work and proposes potential future research directions.

Chapter 2

Literature Review

The shared control problem from perspective of the physical human-robot interaction ([physical Human-Robot Interaction \(pHRI\)](#)) consists of three main processes ([Fig. 2.1](#)) [78]. First, the robot has to identify the intent of the user. The identified intent can provide information to the robot about the user desired goal, so the robot can help the user to achieve that goal. Second, the robot has to arbitrate the control between user and itself with respect to the user intent and the application objectives. Finally, the robot has to provide user with feedback in order to enhance the user adaptation performance. Since I am mainly focused on the robot (exoskeleton) side adaptation rather than human side, feedback process will not be studied in this thesis.

2.1 Intent Detection

Intent detection process consists of three main steps: (1) defining the intent variable, (2) measuring the information related to that variable, and (3) mapping the measured information to the defined intent variable. Each of these processes are discussed in more details in the following sections.

2.1.1 Intent Definition

There are several subsystems contributing to human motor control including the central nervous system ([Central Nervous System \(CNS\)](#)), peripheral nervous system ([Peripheral Nervous System \(PNS\)](#)), and the musculoskeletal system. Each of these subsystems could

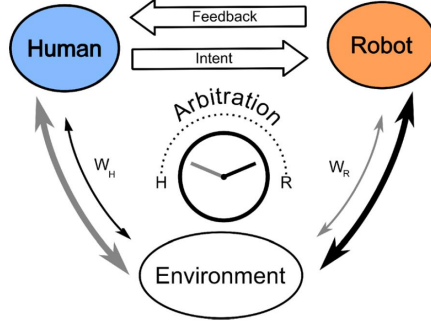


Figure 2.1: Physical human-robot interaction framework consists of human intent, feedback and arbitration elements [78].

be described by a very large set of states which are dynamically interacting with each other, and human intent can be modeled as a function of these states. Depending on the application, however, these states could be reduced to a small subset of variables (intent variable) obtained from partial information of human intent states.

In its simplest form, human intent could be defined as a binary variable like active versus passive or a set of discrete variables. Such intent definition is mostly used for changing the behavioral regime of the exoskeleton controller. In lower limb exoskeletons, for example, [41] has used a brain-machine interface ([Brain Machine Interface \(BMI\)](#)) for detecting human intent in regard to a categorical speed values. Same definition was used to define categorical intents for sitting, walking, or standing in [120].

Continuous intent variables, in comparison to discrete ones, are more informative which results in a more responsive role adaptation of the exoskeleton controller. Continuous intent could be defined at kinematic level (such as desired trajectory or velocity), at force level (such as interaction force), at muscle level such as (electromyography ([EMG](#)) signals), or at neural level (such as electroencephalography ([ElectroEncephaloGraphy \(EEG\)](#)), or ElectroCorticography ([ElectroCorticoGraphy \(ECoG\)](#)) signals).

2.1.2 Relevant Signal Measurement

Neural measurement is mainly performed by measuring the cortex electrical activities in terms of a voltage related to the local field potential ([Local Field Potential \(LFP\)](#)) using electrodes. These electrodes in EEG method are usually placed at the surface of the scalp, while in [ECoG](#) method, they are placed on the surface of the brain in a surgical

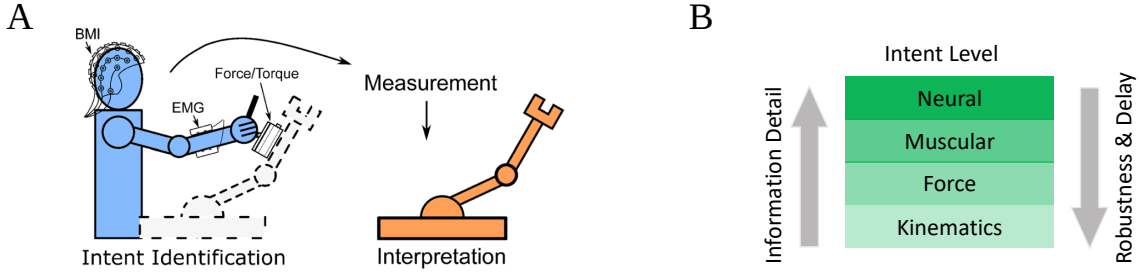


Figure 2.2: Intent detection procedures and levels. (A) Different modalities of intent information which is measured and then decoded (interpreted) by the robot [78]. (B) Robustness and information detail trade off in different intent measurement level.

procedure. In comparison to EEG, ECoG method has higher signal to noise ratio, broader bandwidth (0-200 Hz versus 0-60 Hz), and higher spatial resolution (tenths of millimeters versus centimeters) [70]. Neural measurements with the highest resolution and precision can be measured using intracortical electrodes inserted to the cerebral cortex to record electrical signals generated by neural cells. Disadvantages of intracortical measurement method include its high degree of invasiveness and progressive degradation of the recorded signal quality [132].

Human intention can be also decoded from muscular measurements. The most usual approach in this regard is electromyography (EMG). EMG signals are infact activation of motor units measured using the nearby electrodes. These electrodes are usually attached in a monopolar or bipolar configuration to the surface of the muscle (surface EMG). Bipolar electrodes are in fact several monopolar electrodes attached to different areas of the muscle. Therefore, they can additionally represent spatial information of the muscle activity. Surface EMG measurement tools are easy to install and widely accessible but they are more prone to measurement noise and errors due to replacement and skin properties change such as sweating. Another problem with surface EMG is that not all muscles are accessible form the skin surface. Intramuscluar EMG, on the other hand, measures muscle activities using fine needle electrodes which are directly inserted into the muscle. They are, therefore, more accurate and less prone to replacement and noise with the cost of invasive placement.

Force myography (Force MyoGraphy (FMG)) [14] and sonomyography [1] are other approaches toward muscle activity measurement. The former maps the topological muscle force (or pressure) to its activity while the latter uses ultrasound imaging of muscles to perform the same mapping. Both of these approaches are non-invasive and robust to

the usual noises in [EMG](#). [FMG](#), however, can represent less details about the muscle activity since it does not directly measure motor units activations. Sonomayography is also not computationally cost effective and infeasible in mobile application such as lower limb exoskeleton control.

User intention is also extractable by measuring interaction force using load cells. In case of single interaction point applications (such as upper body therapeutic exoskeletons), loadcells provide the best measurements of the exchange of force in the end-effector. In lower limb exoskeletons, however, human legs are attached to the exoskeleton segments using straps and interaction forces are distributed over these straps. In addition, human-exoskeleton contact is not rigid due to the compliance of human body and straps and that makes the force measurement almost impossible using load cells. In such cases the interaction force is estimated directly using the exoskeleton dynamics [\[27, 53\]](#) or is considered as a disturbance and is indirectly estimated using disturbance observers [\[56, 65, 76, 97\]](#). Alternatively, joint torques could be estimated using ground reaction force and lower limb kinematics assuming that user is able to project his/her intent in these measurements. A disadvantage of indirect torque estimation methods is that dynamics of the human body and exoskeleton are required to be known. The latter is challenging to be obtained accurately especially in case of having exoskeleton motors with high gear ratio transmissions which inject huge static friction to the dynamics.

Movement kinematics data provide another source from which intent information can be extracted. These signals could be accurately measured using a wide variety of equipments including motor encoder, Inertial Measurement Unit (IMU), and optoelectronic motion capture systems. In case of healthy subjects, this information could help robot to predict future motion of the user and provide assistance accordingly. Statistical features of the kinematic information can help the robot compute an intent confidence level which is later useful for role arbitration particularly in impaired subjects. For example in [\[27\]](#), kinematic information is used to compute the geometrical gait cycle percentage. The distribution of the difference between temporal and geometrical gait cycle percentage is then shown to be related to the contribution level of the user to the task. This idea can be further developed and be used in estimation of intent detection confidence. The same information could be also extracted from the distribution of the trajectory tracking error.

It is noteworthy that intent measurement comes with a trade off between information details, delay, and robustness against the measurement noise (see [Fig. 2.2A](#)). From a dynamical system point of view, human intents first emerge at CNS (the deepest level). It is then transformed to muscle activities. Muscle activities generate interaction forces between the user and the exoskeleton which consequently affect the movement kinetics and kinematics (the most superficial level). Accordingly, the deeper the intention is measured

the lesser measurement delay and higher detailed information will be obtained.

2.1.3 Intent Decoding

Generally, the intent information that we wish to know is not always the same as the signals we are able to measure. Therefore, we need to interpret the measured signals to find out the intent information we are looking for. Intent decoding is done by finding a mapping between measured signals and the intent variables. This mapping could be obtained using modeling of human and exoskeleton behavior in different levels depending on the intent information. Furthermore, the intent information could be directly interpreted as explicit human intentions or indirectly interpreted as human desire to change robot's behavior. The latter approach of intent decoding is tightly related to role arbitration.

Neural based intent information which is widely used in BMI applications are mainly mapped into categorical intent variables using various machine learning techniques ranging from simple linear classifier to deep neural networks depending on the extracted features from the EEG data [41, 87]. In [41], for instance, the frequency domain features of EEG signals are classified using linear discriminant analysis method into 4 modes of gait at different speeds.

Myography information is interpreted as categorical or continuous intents depending on the application. Pattern recognition approaches are more useful in mapping extracted features from muscle activity information to discrete numbers of desired robot states or operations [87, 107]. In many applications, however, we are interested in mapping muscle activity features such as amplitude to continuous intent variable. [41], for example, used low-passed versions of Rectus Femoris and Semitendinous EMG signals as inputs of a central pattern generator in order to modulate the gait speed in a dynamical manner. This way, muscle activation information is decoded as the user intent for increasing or decreasing the gait speed. Alternatively, [127] derived an agonist-antagonist actuation system of an exoskeleton joint by proportionally mapping the amplitude of EMG signals of agonist-antagonist muscle pairs to the actuators torque. Although the gains are hand-tuned later, this mapping could be autonomously learned in case of having an estimation of the user desired torque [59]. Despite its simplicity, this approach has a potential to involve the CNS adaptation capacity to minimize the gap between the intended and actual behavior of the exoskeleton. [69].

Another approach for joint torque computation using EMG signals is to identify the Hill's muscle model parameters and compute the joint torque accordingly [35, 131]. A major issue of this approach is that muscle activation of several muscles for each joint needs to

be measured and modeled. This requires identifying a large set of parameters which varies across users. Furthermore, frequent calibration procedures are required to maintain the accuracy of the model since model parameters change due to sensor displacement and skin property changes. An alternative approach for tackling this issue is to use Artificial Neural Networks to map the muscle activation to joint torques. In order to tackle the calibration issue, network training is done with respect to achieving a control objective rather than decreasing the estimation error. Gui et.al. [42] has used this method to train a network for estimation of joint torques in a lower limb exoskeleton application while applying a Slotine-Li trajectory tracking method to the system.

Intent decoding is also possible using kinematic information. Healthy users can represent their intended motion in their kinematic information given that the robot controller provides them with enough freedom. Therefore, it is possible to predict human intent based on the previous kinematic observations [17]. Both of these works used measured position to estimated a minimum jerk, bell-shaped profile of the user’s desired speed that is continuously updated. In case of impaired users, however, it is not safe to rely solely on their kinematic measurements. As a result, their intent is taken into account indirectly in order to adapt exoskeleton trajectory or impedance. Finally, kinematic information combined with force measurement are useful in estimation of the human joint impedance.

Interaction force information is widely used in the framework of pHRI. It could be directly used for estimating the human intended motion [37, 73, 74]. For example, in [74], an impedance model for the human limb was assumed with an equilibrium point equal to the human intended position. They proposed a gradient descent adaptation method to estimate the desired motion by minimizing the interaction force square. In this scenario, the estimated human position is directly used as the reference input for the robot controller. Indirect applications of human intent in force level are later covered in Section 2.2.3.

The human–exoskeleton interaction force is key information that can reveal human intentions [78]. This allows exoskeleton controllers to adjust their behavior to match each individual’s specific needs during therapy or everyday life. Accurate measurement of interaction forces is challenging due to the complex nature of the exoskeleton–user interface, involving multiple contact points such as the feet, shanks, thighs, and torso, making it difficult to isolate and measure the forces transmitted between human and robot [20].

The human–exoskeleton interaction can be modeled in a single-degree-of-freedom (DOF) exoskeleton using a spring–damper system, allowing one to obtain a single dynamical equation describing both human and exoskeleton behavior. For example, human–exoskeleton dynamics were identified in [121] for a one-DOF back-support exoskeleton. A Kalman observer was employed to estimate the interaction torque as a function of system states.

However, obtaining human–exoskeleton dynamics together is not straightforward in exoskeletons with higher DOFs, and the dynamic identification has to be repeated for each user. Therefore, the exoskeleton passive dynamics need to be identified independently. The interaction torque is then computed by subtracting the exoskeleton passive dynamics from the actuation torques (see [27, 53]). Alternatively, disturbance observers could provide a more robust estimation of interaction torques, assuming the human contribution to the gait is an external disturbance [56, 76, 119].

Many previous works on the system identification of lower-limb exoskeletons have primarily focused on identifying dynamics during the swing phase of walking [13, 39, 153], often assuming a simplistic two- or three-link inverted pendulum model for each leg while ignoring the coupling between the hip joints. These simplifications frequently lead to inaccurate interaction torque estimations, particularly during the stance phase of walking. To achieve precise interaction torque estimation throughout the entire gait cycle, it is crucial to identify the exoskeleton dynamics as a whole multibody system.

In contrast to previous work, a comprehensive multibody model considers the complex interactions between the exoskeleton and the user’s body segments, such as the torso. By incorporating these interactions, the model can provide more accurate estimates of the interaction forces and torques exchanged between the exoskeleton and the user throughout the entire gait cycle. Recent studies have identified exoskeleton dynamics as a whole multibody system through a data-driven model that involves exciting the exoskeleton joints with rich torque commands while the exoskeleton is fixed to a rigid supporting platform [154]. However, this approach fails to capture the exoskeleton–environment interaction, which is the supporting force that fixes the exoskeleton to the platform. Consequently, important information about the exoskeleton–environment interaction was ignored, limiting the applicability of these methods for certain exoskeletons. For example, gait training systems such as Locomat (Hocoma, Switzerland), where the hip torque is applied between the femur and a fixed support [140], are better suited for this method than exoskeletons with trunk segments such as Indego (Parker Hannifin, Cleveland, OH, USA), where the hip torque is applied between the femur and trunk, and the interaction occurs primarily between the user’s core and the exoskeleton trunk segment [33]. Therefore, to accurately identify the exoskeleton dynamics and interaction torques, it is necessary to include the exoskeleton–environment interaction in the system identification process.

To address this issue, [118] proposed an approach for identifying exoskeleton dynamics. This method involves learning the joint torques of the exoskeleton using a nonlinear autoregressive network with exogenous inputs (**Nonlinear Autoregressive network with exogenous inputs (NARX)**), based on data collected while the user wears the exoskeleton and applies minimum joint torques. However, this method assumes that the user can

Arbitration	Active	Indirect Intent Dependent Control
		Direct Intent Dependent Control
	Passive	Spatiotemporal decoupling
		Impedance Modulation
	None	Impedance Control
		Pure Trajectory Control

Figure 2.3: Control arbitration levels based on their dependency on intent information.

completely disable their contribution to the motion, which is not feasible in legged locomotion where maintaining stability is crucial. Moreover, the identified dynamics are a combination of the exoskeleton dynamics and the passive dynamics of the user, requiring the identification process to be repeated for each new user.

2.2 Arbitration

Arbitration refers to sharing of the control between human and exoskeleton. In [pHRI](#) applications, the robot has to adapt its level of dominance based on the human performance. Level of dominance regulation in exoskeleton applications is mostly done by adjusting the impedance properties of the exoskeleton or its reference trajectory. The level of dominance varies between two extreme levels [\[40\]](#). In the lowest level, the robot has no role in completing the task (passive follower) while in the highest level the opposite applies (active leader). Agent’s level of dominance in shared control tasks is adjusted according to specific strategies called roles. Different roles could be considered as different cost functions which in the simplest form are a sum of error and effort norm of either human or robot. Within this framework, the level of dominance is regulated with respect to the minimization of each agent’s cost function at a Nash equilibrium point [\[51\]](#). Role arbitration, therefore, could be seen as modification of the robot cost-function.

Investigating the literature, it is noticed that the existing exoskeleton controllers do not necessarily include the role arbitration feature. Conventional controllers including trajectory and impedance control have no role arbitration (the robot role is always fixed).

It is shown that pure position control strategy is not effective for iSCI rehabilitation since it does not encourage users to actively contribute to the motion [49]. Therefore, the user either passively follows the exoskeleton or fights back depending on their impairment level. Obviously, none of these situations are favorable unless for early stages of rehabilitation when users cannot actively contribute to the task performance.

In order to tackle this issue, role arbitration feature was incorporated in the design of assistive and rehabilitation controllers which has led to the concept of Assist-As-Needed (AAN) controllers. AAN controllers try to provide the minimum required support to the user in order to maintain a sustainable level of challenge for the user to perform gait. This strategy promotes neuroplasticity which in long term can lead to neural control recovery. AAN partially assists patients while allowing voluntary active movements, and maximally engage their neuromuscular system [27,155]. Role arbitration in AAN controllers take place in passive or active form. Controllers with passive arbitration adjust the robot's level of dominance by modulating the impedance and decoupling spatial and temporal control based on human performance measure regardless of the human intent. AAN methods with active role arbitration, on the other hand, share the control with the user according to the human intent.

2.2.1 Conventional Controllers Without Arbitration

Position Controller

Position control is the very first control approach used for lower limb exoskeletons. In this method, the exoskeleton joint trajectories are controlled on a predefined sets of trajectories. The controller goal is to reduce the trajectory tracking error regardless of the control effort. This is mainly done by combining a feedback and feedforward control scheme. Any contribution of the user to the motion is considered as a disturbance unless it is consistent with the controller effort. This controller scheme works well for users who cannot contribute to the motion considerably. For individuals with residual motor control, however, this controller is mostly disruptive than beneficial since often, their contribution to the motion is not consistent with the applied torques by the user (or trajectories) resulting in a conflict between human and the exoskeleton. Since there is no adaptation capacity considered for the controller, it is to human to adapt himself/herself to the robot to resolve this conflict. This adaptation in human leads to yielding the control to the exoskeleton and not contributing to the motion. Therefore, the capacity of the user is ignored and their participation is discouraged in this scheme while an effective control strategy should incentivize the user to engage in performing the task as much as possible.

Impedance Control

Impedance control (combination of position and force control) is used [45] in order to enhance the performance of pure position control in exoskeleton control. Impedance control has the ability to endure a divergence from the reference trajectory in presence of an external force which in our study is mostly the force applied by the user. This capacity which is called compliance gives us a degree of freedom to allow user contribution in the gait. This approach, however, imposes a trade off to the controller design between spatiotemporal guidance and freedom. In other words, if I use a stiff setting for compliance, a solid trajectory is imposed to the user while he/she cannot contribute to the motion. In contrast, if the compliance is too soft, user has more freedom comparatively but I cannot correct his/her movements where it is needed. This has led to the development of AAN controllers with passive arbitration approaches which enrich the impedance control by autonomously modulating the system compliance with respect to gait state and user performance.

2.2.2 Passive Arbitration

As mentioned previously, impedance control by itself cannot satisfy an efficient rehabilitation performance. Two main drawbacks of impedance control are spatiotemporal coupling and lack of impedance variability. Here, I investigate the main approaches for tackling these issues.

Spatiotemporal Decoupling

Instead of controlling trajectory or force directly, a relation (usually linear) between them is controlled in impedance control scheme. This approach, therefore, imposes an inherent coupling between system position and its behavior in presence of external force. Using time-based trajectories in this scheme leads to spatiotemporal coupling which constrains the user from altering his/her gait pattern and timing independently. One solution is utilization of a time-independent reference trajectory. In this approach, reference trajectories are defined in terms of gait cycle parameter (S) which is monotonically increasing during each stride and is related to the system states rather than time explicitly. For example, [143] has used the stance leg's ankle joint angle as such state for controlling a bipedal robot.

Finding a monotonically increasing variable in terms of system state is not always feasible, especially when it comes to gait control. Alternatively, researchers have used geometrical methods for estimating S by finding the closest point on the reference trajectory

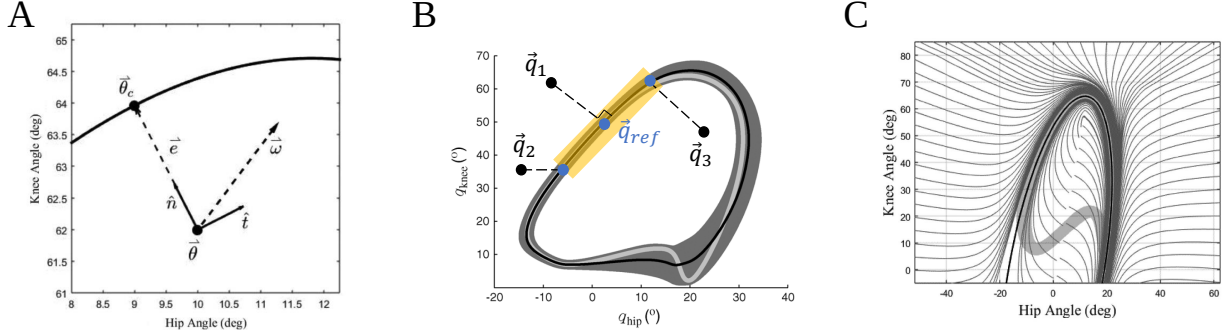


Figure 2.4: (A) Finding the reference position $\vec{\theta}_c$ by orthogonal projection of current joint position $\vec{\theta}$ to the geometrical reference path regardless of time. $\hat{n}$ is the unit error vector and $\hat{t}$ is the tangential vector to the reference trajectory curve. $\vec{\omega}$ is also the spatial joint velocities ($\vec{\omega} = d\vec{\theta}/dS$) [83]. (B) Variable error dead-zone around the reference trajectory (gray area) and time-dependent velocity constraint on the motion where the $\vec{q}$ (joint position) is constrained to be projected within the back and front time-walls (the yellow area). For example, orthogonal projection of q_1 is between the back and front time-walls (yellow area), so the reference position is the same as the projected point. q_2 , and q_3 projections are, in contrast, outside of the back and front time-walls, so their corresponding reference positions are limited to the position of back and front time-walls, respectively. Exoskeleton reference trajectory (black curve) complexity is also reduced in comparison to the real human gait trajectory curve (light gray) [27]. (C) Velocity field design based on weighted combination of error ($\hat{n}$) and the tangential ($\hat{t}$) vectors [83].

curve to the current position of each leg. S is then computed based on the obtained reference position index. In this method, the reference position is found regardless of time (see Fig. 2.4A) [60].

Velocity Flow Control (VFC) [72] is another approach proposed for spatiotemporal decoupling. In this approach a forgiving velocity controller is set to track desired velocity values instead of position references. The spatial profile of the desired velocity is shaped, however, to represent the desired trajectories (see Fig. 2.4C). Since the desired velocities are function of kinematics rather than time, temporal freedom is achieved using this approach [4, 5, 83].

Both Path Control and VFC methods are based on estimation of gait cycle variable (S) which is found using the projection algorithm. One drawback of this approach is that the obtained S is prone to instability and jumps, particularly in transitions between swing and stance phases. As a result, complexity of human natural gait is reduced in Path Control

and VFC methods (Fig. 2.4B, C) and gait control is disabled during stance phase where exoskeleton support is still required.

Gait phase estimation has been widely used in control of assistive technologies such as lower-limb exoskeletons [80, 135], also in gait neuromechanical modeling and analysis such as joint impedance identification [3, 63] or estimation of gait spatiotemporal parameters [145].

Accurate real-time gait phase estimation is challenging, particularly, in case of pathological gait patterns. Obtaining an accurate estimation of the gait phase is largely dependent on predicting the next gait event’s timing. Typically, the gait phase is estimated by the ratio of the elapsed time from the latest heel-strike over the expected stride duration. [68, 71]. As the estimated stride duration is updated at the end of each step, this method is only appropriate for conditions with low variability in gait.

To address this issue, gait phase has been redefined and usually estimated according to joint angles or the body motion. In [46, 106], for example, the phase-shift between the hip joint angle and its integral is interpreted as the gait phase. In [111, 151, 152, 156], a cluster of adaptive oscillators (**Adaptive Oscillator (AO)**) is employed to lock to the hip angle phase and frequency or variation of leg’s muscle shapes. Alternatively, a Kalman filter (**Kalman Filter (KF)**) is used in [135] instead of AOs to estimate the gait phase. In these methods, gait speed changes are continuously reflected in the gait phase, however, with some lag due to the AO or the KF convergence dynamics. A solution is to reset the estimated gait phase to zero at each heel-strike, detected using a contact sensor. Such instantaneous correction of the gait phase error, leads to discontinuous estimation. The phase error is, therefore, gradually corrected to maintain the smoothness of the gait phase [152].

A more accurate gait phase estimation, nevertheless, requires more joints to be involved in the estimation process. As an example, the gait phase is estimated in [2] by finding a point on the hip-knee reference path that has the minimum distance from the current hip-knee coordinate. To include more kinematic features (e.g., joint velocity or body segments acceleration) data-driven models are widely used as they can learn the mapping from multi-dimensional kinematic space to the gait phase. A Robust estimator, on the other hand, is expected to provide an accurate mapping in a wide range of gait speeds, patterns, conditions, and user characteristics. Artificial Neural Networks (**Artificial Neural Network (ANN)**) have the capability of learning such complex mapping.

In [54], for example, an ANN is used to estimate the gait phase at different speeds from the hip joint angle and trunk and thigh inertial measurement units (**IMUs**) measurements. Alternatively, long-short-term-memory (**Long Short Term Memory neural network (LSTM)**) networks are used to learn the gait phase from the IMU data [64, 113, 116]. Addi-

tionally, [55] uses a convolutional neural network ([Convolutional Neural Network \(CNN\)](#)) to estimate the gait phase while accounting for the variable gait patterns associated with stairways and ramps.

Using data-driven models, the problem of designing a robust and accurate gait phase estimator is turned into the problem of collecting a rich data set that enables the model to capture a generalizable yet accurate mapping between input data and the gait phase. The need for a specially designed and trained gait phase estimator is even more critical for gait training exoskeletons because they must be capable of assisting a broad spectrum of pathological gait patterns. The natural conflict in physical human-exoskeleton interaction also require extra robustness. Therefore, acceleration or velocity data, which have a higher sensitivity to emerging conflicts, have to be avoided as input features making the gait phase estimation even more difficult.

Currently, none of the existing studies are designed to provide accurate phase estimation during abnormal or pathological gait. They are also designed specific to a certain exoskeletons or prosthetic device.

In case of using spatiotemporal decoupling approaches for disabled people, temporal freedom needs to be restricted depending on their motor deficits by imposing a constraint to the system velocity. This is more straightforward in VFC method since it is inherently a velocity controller. This issue in Path Control method is tackled by simply limiting the lower and upper bound of S by sandwiching it between two monotonically increasing time dependent profiles [27]. This is like a set of back and front-wall that push the user forward and backward if he/she is not moving fast or slow enough, respectively (see [Fig. 2.4B](#)). Otherwise, it does not affect the user.

A shortcoming of time-wall method is that it does not consider the human intention in acceleration or deceleration of the gait. Another contribution of my PhD thesis is to include human intention extracted from muscle activation or kinematic measurements to adapt the back-wall constraint. I am also going to develop a gait speed predictor which is useful in designing the desired velocity field properties in the [VFC](#) method.

2.2.3 Active Arbitration

As previously discussed, intent information can be directly used for determining the user desired trajectory or applied force directly. In such cases, these information are simply utilized as the robot controller reference inputs [74]. This approach is, however, applicable upon existence of high confidence on the decoded intent which is not always achievable particularly when it comes to rehabilitation and assistive exoskeletons. Therefore, in most

of the applications, intent information indirectly affects the controller by adapting the reference trajectory or the controller impedance. In this scenario, instead of estimating the human intended motion or impedance directly, the robot’s reference trajectory or impedance is adjusted according to the intent information or adapted with respect to minimization of a cost function defined over the intent information. This adaptation is usually being controlled by a confidence factor showing the reliability of the intent information.

With respect to controller impedance adaptation, [75] employed a cost function that is the weighted sum of the robot’s applied force, interaction force between user and robot, and tracking error. Assuming that the human has the same cost function, the optimal actuator torques and interaction forces at the Nash equilibrium are computed as functions of the cost-function weights. These weights are then adapted with respect to minimization of the difference between actual and the optimal interaction force which is considered as the intent information. It is shown that adaptation of the cost function weights in this approach is equivalent to adaptation of the the robot impedance. An increase in the interaction force, therefore, leads to a decrease of robot’s impedance and vice versa.

In [88], an approach is introduced to use the intent information and their statistical features. An optimal control scheme is then used in order to find the optimal robot torque in a limited horizon using Linear Quadratic Regulator ([Linear Quadratic Regulator \(LQR\)](#)). Intent information is included in the definition of the cost function such that the robot hands over the control to the user where there exist higher variability (which is interpreted as disagreement) in the motion and in the interaction force.

Exoskeleton trajectory modification is another active arbitration method in [AAN](#) controllers with active arbitration. In its simplest form, it could be done using heuristic approaches. For example, in [84], the controller adjusts the swing trajectory based on the joint positions at the late stance phase. A more systematic framework, however, is to adapt the trajectory with regard to minimization of the interaction force, exoskeleton’s applied torque, or tracking error [29,30,53,110,112,137,148,155]. For instance, [53] presented three different control strategies for minimizing the interaction force between exoskeleton and patient. Also in [30], an [AAN](#) control method is proposed where the swing phase trajectory is adapted by online minimization of applied force and position error.

In active arbitration framework, the main assumption is that the user can generate reliable intent information. Therefore, any trajectories or impedance setting that minimizes the cost function is an acceptable solution. This is not necessarily a valid assumption for the whole spectrum of [iSCI](#) individuals and we cannot always rely on their exhibited trajectory. This issue is already discussed in [53], where the adaptation method converged to nonphysiological patterns for impaired cases or in [27], where it is shown that some of

the impaired users relied on the tunnel boarders (which means relying on robot assistance) in order to be able to walk.

2.3 Human-Exoskeleton Physical Interaction Evaluation

Despite recent advancements, including human-in-the-loop optimization to improve exoskeleton assistance [10, 26, 36, 104], exoskeletons still lack the sophistication to automatically fine-tune the level of support required for each individual user effectively [66, 98]. This personalized touch, instinctive for physical therapists in traditional therapy sessions, remains a challenge for robots. The challenge arises because, although separate performance indicators like metabolic cost [105, 147], muscle activation [82, 157], interaction forces [61], comfort [32], cognitive load [85], and user preference [48] are utilized, the lack of a unified metric that fully encapsulates the nuances of human-robot physical interactions obstructs the precise adjustment and customization of lower limb exoskeleton support [103]. Therefore, this task is often delegated to adaptive controllers with implicit considerations to control the human-exoskeleton physical interaction. The control of human-exoskeleton interaction plays a key role in optimizing the user experience and performance of lower limb exoskeletons for rehabilitation as well as power augmentation applications [125]. In power augmentation scenarios, the user retains full autonomy, and the exoskeleton follows user commands directly or indirectly by interpreting their intended motion. In case of disagreement between the user and the exoskeleton, the exoskeleton must relinquish control in favour of the user [83, 88]. However, in the context of rehabilitation and assistive exoskeletons, human-exoskeleton interaction control is more challenging due to two primary factors. First, the user-performed motion is not always reliable due to musculoskeletal or motor impairments [124] which may undermine the quality of decoded intention solely based on user-robot physical interaction. Second, the exoskeleton should encourage the user to maximize their engagement in motion when possible and assist or correct when the user is unable to perform the motion correctly [6, 25]. Consequently, the exoskeleton must seamlessly transition between the leader and follower roles [78].

To determine the appropriate control strategy for human augmentation and rehabilitation applications, it is crucial to understand human-exoskeleton adaptation as an indicator of how individuals respond to specific exoskeleton control strategies concerning shared motion control [50]. In power augmentation, the ideal scenario involves users adapting to a strategy in which they contribute primarily by guiding the motion, without physical exertion [26]. The exoskeleton takes the responsibility of moving the human body by applying interaction torques or forces to the human body, as demonstrated by reduced

muscle activity or metabolic rates [36]. Conversely, in rehabilitation, users must often be guided to increase their muscle activity and actively engage in motion control [8]. The human-exoskeleton interaction torques exhibit a dual behavior in this context. When the user performs the motion correctly, the exoskeleton must transparently follow the user, resulting in zero interaction torques [61]. However, when motion correction is required, the exoskeleton controller should intervene. This intervention creates a conflict necessitating an increase in the interaction torque to rectify the motion. Neither muscular effort nor interaction torques alone can discern the aforementioned conditions. For example, an increase in muscular effort may stem from human-exoskeleton disagreement [124], while it can also signify that the human user is engaged in walking and relies on their motor capacity rather than on exoskeleton assistance. Therefore, to compare different controllers in such cases, interaction torque needs to be considered alongside muscular effort. A low level of interaction torque coupled with higher muscular effort suggests no physical disagreement, indicating that the exoskeleton is following the user and the user is walking with minimal assistance. Otherwise, a higher level of interaction torque along with high muscular effort indicates that the user and exoskeleton do not share the same desired motion patterns, and they are fighting for control [78]. Therefore, determining the suitability of a controller for either power augmentation or rehabilitation applications necessitates co-analysis of muscular effort and interaction torque.

Chapter 3

Ultra-Robust Real-Time Estimation of Gait Phase

An ultra-robust accurate gait phase estimator is developed by training a time-delay neural network (D67) on data collected from the hip and knee joint angles of 14 participants walking on a treadmill and overground. Collected data include normal gait at speeds ranging from 0.1m/s to 1.9m/s and conditions such as long stride, short stride, asymmetric walking, stop-start, and abrupt speed changes. Spatial analysis of our method indicates an average [RMSE](#) of $1.74 \pm 0.23\%$ and $2.35 \pm 0.52\%$ of gait phase on test participants in the treadmill and overground walking, respectively. The temporal analysis reveals that D67 detects heel-strike events with an average MAE of $1.70 \pm 0.54\%$ and $2.74 \pm 0.92\%$ of step duration on test participants in the treadmill and overground walking, respectively. Both spatial and temporal performances are uniform across participants and gait conditions. Further analyses indicate the robustness of the D67 to smooth and abrupt speed changes, limping, variation of stride length, and sudden start or stop of walking. The performance of the D67 is also compared to the state-of-the-art techniques confirming the superior and comparable performance of the D67 to techniques without and with a ground contact sensor, respectively. The estimator is finally tested on a participant walking with an active exoskeleton, demonstrating the robustness of D67 in interaction with an exoskeleton without being trained on any data from the test subject with or without an exoskeleton.

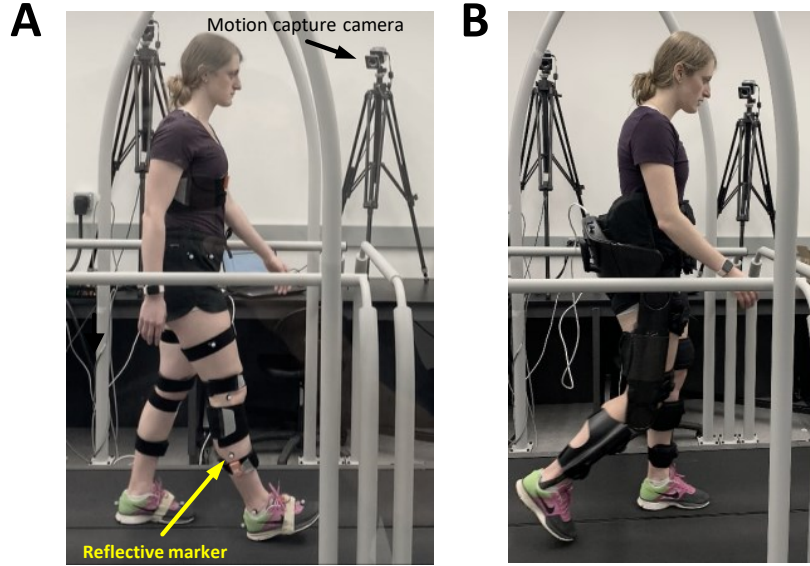


Figure 3.1: Experimental setup: a participant walking on the treadmill (**A**) without and (**B**) with an exoskeleton. Participants kinematics are recorded using the motion capture and motor encoders during without and with exoskeleton walking, respectively. The ground reaction forces are collected by separate load cells under each belt of the treadmill. The participant has permitted usage of their photo in this paper.

3.1 Methods and Material

3.1.1 Experimental Setup

Measurements of lower-limb kinematics were carried out with a motion capture system that included eight Vero Cameras (Vicon, UK). The motion of the lower limbs was calibrated, labeled, and tracked using 16 reflective markers according to the Plug-In Gait convention [92]. An instrumented split-belt treadmill (Bertec, US), capable of measuring ground reaction forces (GRF) under each foot, was used to monitor and control the speed of each belt (Fig. 3.1A). The treadmill and the motion capture data were synchronized and recorded at 1KHz and 100Hz, respectively. A lower-limb exoskeleton (Indigo, Parker Hannifin, USA) with actuated hip and knee joints was also used, worn by an able-bodied individual, to test the performance of the gait phase estimator in the presence of an exoskeleton. The exoskeleton sensory data as well as control commands are transmitted at 200Hz.

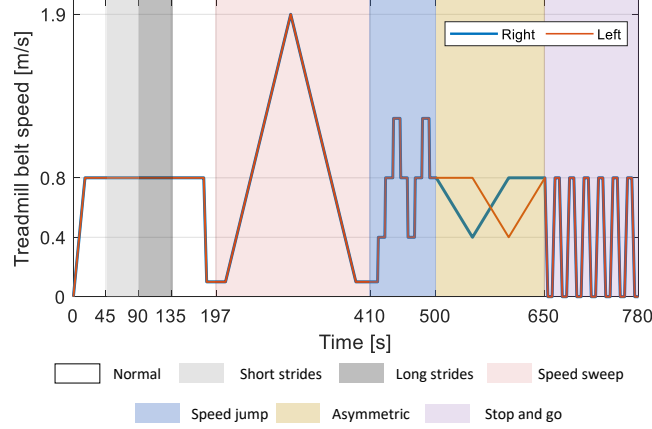


Figure 3.2: The speed profile during the treadmill walking session. The right and left belts share the same speed profiles except during the asymmetric walking condition.

3.1.2 Experimental Protocol

Fourteen participants (age: 28 ± 4 years, body mass: 75.2 ± 17.6 kg, height: 176.6 ± 6.8 cm, 7 females and 7 males) with no known musculoskeletal impairments participated in this study. All participants provided informed consent prior to the experiment. The study protocol and procedures were approved by the University of Waterloo Clinical Research Ethics Committee (ORE#41794) and conformed with the Declaration of Helsinki.

The experiment involved treadmill and an overground sessions. The treadmill session consisted of walking without the help of handrails in 8 different conditions for a total of 13 minutes (see Fig. 3.2). The first four conditions of the test consisted of walking at a constant speed of 0.8 m/s where the participants were asked to walk normally, with short strides, with long strides, and then again normally (for 45 seconds each). The fifth condition of the test included a speed sweep where the treadmill speed increased from 0.1m/s to 1.9m/s with a constant acceleration of 0.02m/s^2 , immediately followed by a constant speed decrease back to 0.1m/s at the same rate. The sixth condition involved speed jumps between 0.4m/s, 0.8m/s, and 1.2m/s. The acceleration of the treadmill during these jumps was 0.4m/s^2 . The seventh condition involved asymmetrical walking. Gait asymmetry was imposed by driving the treadmill belts with different speeds, up to a speed difference of 0.4m/s. As one of the most prominent asymmetric features observed in post-stroke patients, we used the swing time ratio ($t_{\text{longer}}/t_{\text{shorter}}$) for validation of the protocol [101, 136]. The speed difference between treadmill belts was chosen to have a maximum swing time ratio of 1.41 ± 0.19 on average for all participants falling within the

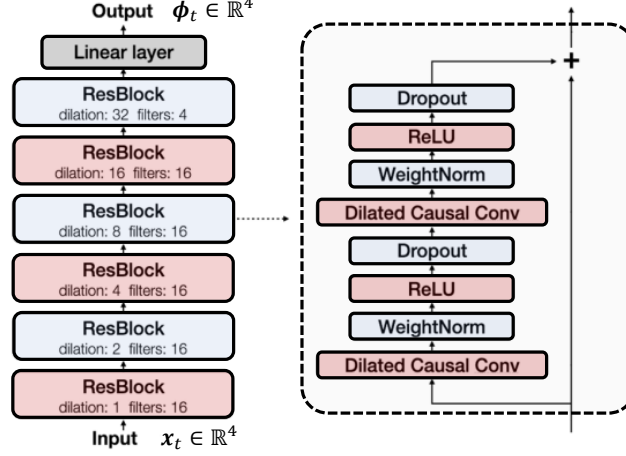


Figure 3.3: The TCN network consists of six residual blocks, each including two dilated convolutional layers with the same dilation factor. Instantaneous joint angles ($\mathbf{x}_t$) are fed into the first residual block while the output of the last residual block is fed into a linear layer to generate the final gait phase predictions (ϕ_t). The dropout rate is set to 0.1 for all residual blocks. Kernel size of 3 is used for all dilated causal convolutional layers.

reported average values of 1.24 [101] and 1.44 [136]. The eighth and final condition involved repetitions of start walking, at a speed of 0.8m/s, and stop walking.

To check the sensitivity of the developed gait phase estimator to the exoskeleton dynamics and its controller effect, one participant repeated the same experiment two more times while wearing the exoskeleton; once in the Passive mode (controller was off) and once in the Active mode (controller was on). In the Active mode, the exoskeleton joints were controlled using the trained gait phase estimator embedded in a path controller [27] with the following joint stiffness (K) and damping (D) coefficients: $K_{\text{Hip}} = 300 \text{ N.m.rad}^{-1}$, $D_{\text{Hip}} = 45 \text{ N.m.s.rad}^{-1}$, $K_{\text{Knee}} = 65 \text{ N.m.rad}^{-1}$, $D_{\text{Knee}} = 25 \text{ N.m.s.rad}^{-1}$. The same impedance values were used for both legs. The reference path was taken from [144].

The overground session consisted of walking on a 10-meter straight path, three times with the following conditions: normal walking, slow walking, fast walking, short strides, and long strides. The participants were instructed to walk at a self-selected pace and adjust as they see fit for the trials at faster and slower speeds.

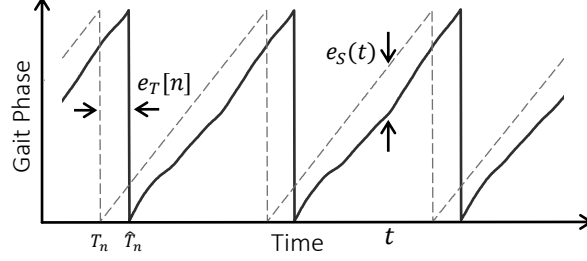


Figure 3.4: Spatial (e_s) and Temporal (e_T) error according to the estimated and target gait phase profiles. The temporal error (e_T) is computed at the n^{th} heel-strike event.

3.1.3 Training and Evaluation of the Gait Phase Estimator

Collected data, including joint angles, marker positions, and [GRF](#) were filtered using a Woltring filter [149]. A Boolean stance flag, $S(t)$, is then computed as

$$S(t) = \text{sgn}(\max(F_{GR}(t) - F_{th}, 0)) \quad (3.1)$$

where $F_{GR}(t) \geq 0$ is the vertical [GRF](#) and F_{th} is a threshold set to 0.01 of each participant's weight. The heel-strike event is then detected from the rising edge of the stance flag. The heel-strike events in overground walking, when GRF was not measured, was extracted by applying the Foot Velocity Algorithm ([Foot Velocity Algorithm \(FVA\)](#)) [100] on the foot marker data. The target gait phase (y) is then determined according to [144] as a monotonically increasing line going from 0 to 1 between two consecutive heel-strikes. The toe-off event is excluded from gait phase generation since its specific phase is not predetermined. If we assume a fixed phase for toe-off (e.g., 0.63), the target gait phase becomes bilinear, causing discontinuities in the controllers designed based on the gait phase.

The target gait phase values are then transformed to an extended description as $\phi = [\phi_1, \phi_2, \phi_3, \phi_4]^T = [\sin(2\pi y_R), \cos(2\pi y_R), \sin(2\pi y_L), \cos(2\pi y_L)]^T$ before being utilized in the training of gait phase estimator. Such transformation avoids the sharp gait phase transition in the 0 to 1 representation which is easier for a data-driven model, e.g., a neural network, to represent. A time-delay neural network [142] with 67 input delays (D67 network) was trained separately using the scaled conjugate gradient backpropagation algorithm [89] to learn the mapping from both legs' hip and knee joint angles (input: $\mathbf{x} = [\theta_{\text{Hip},R}, \theta_{\text{Knee},R}, \theta_{\text{Hip},L}, \theta_{\text{Knee},L}]^T$) to the extended target gait phase (ϕ) by minimizing a loss function of the mean square error ([Mean Square Error \(MSE\)](#)) between the estimated and the target extended gait phase. We note that our model is not sensitive to the method by which the joint angles are computed as long as they are accurate enough. For example,

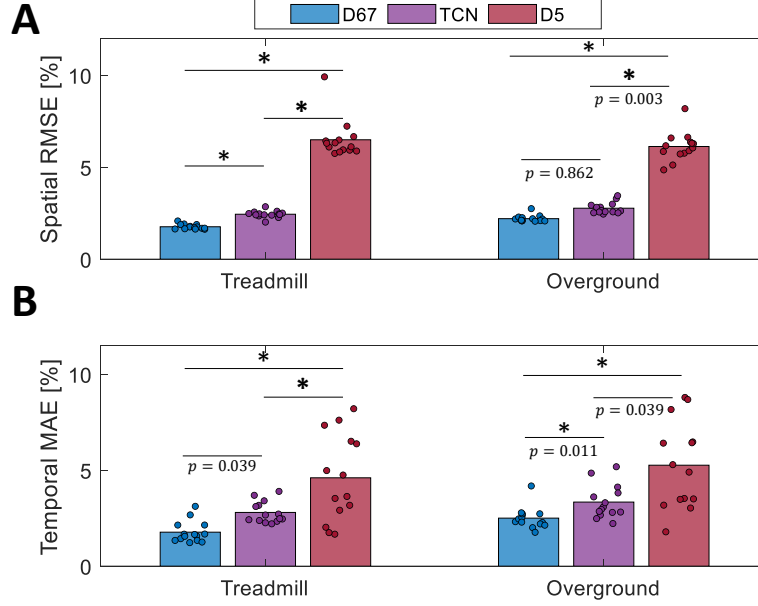


Figure 3.5: (A) Spatial Accuracy comparison between the D67, TCN, and D5 networks. The circles in each pair of network and condition indicate the mean of spatial RMSE across all gait cycles of each participant in all conditions. The average spatial RMSE across the subjects is also represented with the respective bar height. Similarly, (B) compares the temporal MAE of the three networks in treadmill and overground walking conditions. The comparisons denoted by asterisks show significant difference between the average performance of the compared networks. The p -value is smaller than 0.001 unless specified.

motor encoders are later used instead of motion capture to measure joint angle in an exoskeleton-assisted walking scenario(Section 3.2.2). Moreover, since distal joints are more impaired in people with incomplete spinal cord injury, the ankle joint angles are excluded to decrease sensitivity of the trained model. The D67 network consisted of three hidden layers of 30, 20, and 10 neurons with Relu activation functions. The input data to the network is $\mathbf{X} = [\mathbf{x}, \mathbf{x}_1, \dots, \mathbf{x}_{67}]$ where $\mathbf{x}_n$ is the joint angles delayed by $d_n = \sum_{i=1}^n 1 + \lfloor 1.1^i/15 \rfloor$ samples where $\lfloor \cdot \rfloor$ is the floor operator. This way, the sampling density is decreased for older samples enabling the network to increase its memory horizon up to 473 samples (2.365s). For example, in a normal gait with 1.23s step time duration, the first 50 inputs of the network are sampled from the last half-step-time, while only 8 inputs are sampled with more than a step-time delay.

Besides the D67 network, we constructed two baseline networks. The first one is a

Temporal Convolutional Network (TCN), i.e. a modern convolutional architecture capable of capturing long-term dependency of the input similar to recurrent networks while maintaining high computational efficiency of the convolutional operations [62]. Our TCN formulation as well as network hyper-parameters can be found in Fig. 3.3. Instantaneous joint angles ($\mathbf{x}(t)$) are used as an input to the TCN while the dilation factors are increased exponentially across the residual blocks to ensure wide receptive fields. The number of residual blocks is chosen such that the receptive field of the neurons in the last dilated causal convolutional layer covers roughly the period of one full gait cycle. The second baseline network is a time-delay neural network with two hidden layers of 5 neurons with 5 input delays (D5 network). Compared to the previous studies such as [15, 55] which have a 0.3s of sampling buffer, the D5 network has only a 0.025s of sampling buffer, serving as a model with minimum complexity to evaluate if employing more complex network architectures is worth the performance improvement.

We used leave-one-subject-out cross validation to test the neural network’s performance on each subject (training on 13 subjects’ data, testing on one, and repeating the process for all fourteen subjects). Training was performed using treadmill and overground walking data of twelve subjects for updating the neural network weights, while training stop condition was checked using one randomly selected subject. Walking data with exoskeleton are not included in training or validation but are kept apart to evaluate the the estimated gait phase sensitivity to the possible effects of the exoskeleton dynamics and controller. The network estimate ($\hat{\phi}$) is then transformed to the vector of left and right gait phases $\hat{\mathbf{y}}$ using

$$\hat{\mathbf{y}} = 0.5 + \frac{1}{2\pi} [\text{atan2}(\hat{\phi}_1, \hat{\phi}_2), \text{atan2}(\hat{\phi}_3, \hat{\phi}_4)]^T. \quad (3.2)$$

The instantaneous spatial gait phase estimation error is defined as $\mathbf{e}_S(t) = \mathbf{y}(t) - \hat{\mathbf{y}}(t)$. The spatial root mean square error (RMSE) of gait phase estimation over each gait cycle is then computed to compare the spatial performance of the networks. The temporal error is also defined as $\mathbf{e}_T[n] = T_n - \hat{T}_n$ where T_n and $\hat{T}_n$ are the n^{th} heel-strike time detected from target and estimated gait phase, respectively. $\mathbf{e}_T[n]$ is then divided by the duration of n^{th} stride (separately for the left and the right legs) to normalize the temporal error across different conditions (e.g., long or short strides). Temporal mean absolute error (Mean Absolute Error (MAE)) is used as a compact measure for between-network comparisons. The statistical differences are identified by applying a two-sample Kolmogorov-Smirnov test with a significance level set to 0.05 with a Bonferroni correction being applied when comparing the three networks.

Table 3.1: Comparison of D67, TCN, and D5 network Performances.

Session	Network	Spatial RMSE [%]	Temporal MAE [%]
Treadmill Walking	D67	1.74 ± 0.23	1.70 ± 0.54
	TCN	2.57 ± 0.79	2.87 ± 0.55
	D5	6.41 ± 3.30	4.37 ± 2.27
Overground Walking	D67	2.35 ± 0.52	2.74 ± 0.92
	TCN	2.69 ± 1.40	3.65 ± 1.35
	D5	6.33 ± 3.47	5.26 ± 2.32

3.2 Results and Discussion

The overall spatial and temporal performances of D67, TCN, and D5 networks on the test participants across all trials are compared in Fig. 3.5 and Tab. 3.1. The D67 network outperforms the TCN network with 32.3% and 39.3% smaller spatial and temporal errors during the treadmill session, respectively. The D67 also exhibits 24.9% smaller temporal MAE in overground walking. The spatial performance, however, is not significantly different between the D67 and the TCN networks during the overground session. D67 network significantly outperforms the D5 spatially and temporally in treadmill walking and spatially in overground walking. The similar observation applies to the TCN except for the temporal performance during the overground walking. In all cases, D67 and TCN have a more uniform spatial and temporal performance across all participants, confirming the generalization of the trained models. D5 performance, in contrast, has greater variations, particularly, in terms of temporal MAE implying the lack of expressivity in D5.

3.2.1 Detailed Performance Analysis

We now focus on D67 network for more detailed analysis of gait phase estimation performance across different conditions in both treadmill and overground walking.

Treadmill walking

Fig. 3.6A shows the average estimated gait phase spatial profile with respect to the target gait phase across all gait cycles in different conditions in treadmill walking. The coefficient of determination for the estimated gait phase is greater than 0.999 that along with its negligible standard deviation confirm the accuracy and generalization of the D67 network.

The spatial performance across different experiment condition is further investigated in Fig. 3.6B where the mean Spatial RMSE is plotted for each participant along with the

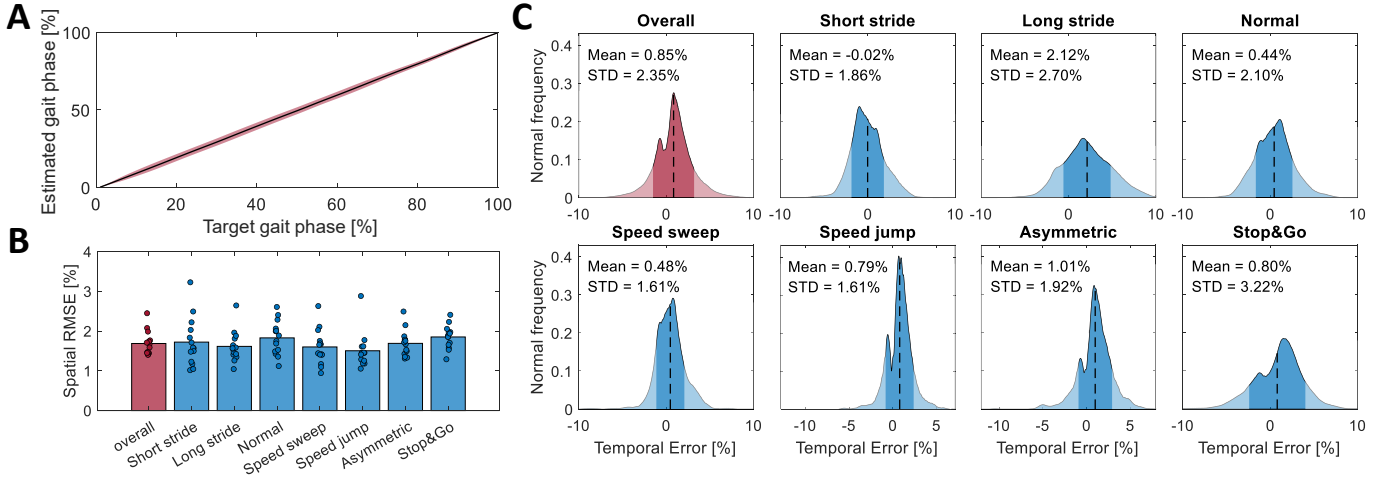


Figure 3.6: The performance of the D67 network in treadmill walking gait phase estimation. (A) the average estimated gait phase profile with respect to the target gait phase. Gait phase estimation standard deviation is shaded in red. (B) the spatial RMSE of the estimated gait phase across the strides in each condition made by all participants. The average RMSE of gait phase estimation at each condition is represented by the respective bar height. (C) the estimated gait phase temporal error across all participants in each condition. The mean and standard deviation of the temporal error are depicted by dashed lines and bold areas, respectively.

total mean Spatial RMSE across all participants in each condition. The standard deviation of mean performance across all conditions is 0.12%, indicating consistent generalization of the D67 model over experiment conditions.

Fig. 3.6C illustrates the distribution of the temporal error across experiment conditions. The D67 has accurately detected heel-strike events on average 0.85% earlier (e.g., about 10ms earlier in a stride with duration of 1.2s). The leading temporal estimation is, however, not consistent as the multimodal distribution of temporal error reveals that the estimated heel-strike event lags behind the actual event rather than leading for a sub-group of participants and conditions. The magnitude of the temporal error is, nevertheless, consistently small in treadmill and overground sessions across all experiment conditions showing the accuracy of D67 in heel-strike detection based on the hip and knee joint angles.

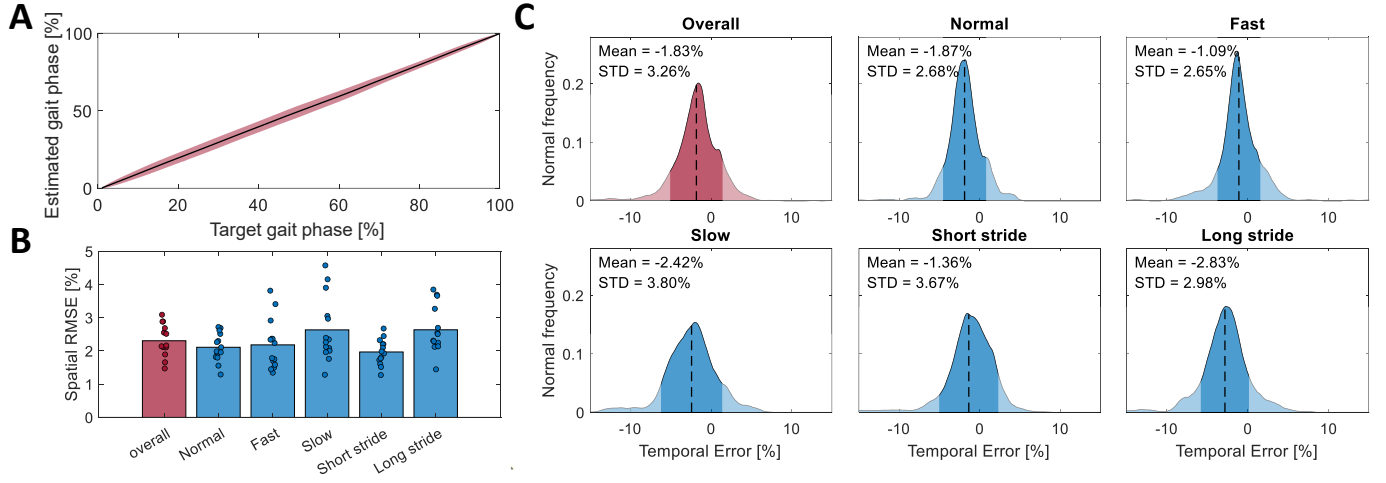


Figure 3.7: The performance of the D67 network in overground walking gait phase estimation. Figure description is the same as Fig. 3.6.

Overground Walking

The average estimated gait phase profile across all gait cycles in different conditions during overground walking is depicted in Fig. 3.7A showing a slight increase in standard deviation compared to the treadmill walking. Fig. 3.7B provides further details on the spatial performance for each participant across different conditions, indicating the D67 network's consistent performance.

In contrast to the treadmill session, the heel-strike detection takes place with a small but consistent lag during the overground walking. Fig. 3.7C illustrates that the heel-strike event is detected -1.83% later than the actual event (e.g., about 21ms later with a 1.2s stride time). This implies that the controlled condition in treadmill walking enables the model to better capture the gait dynamics and therefore, predict the heel-strike accurately. Moreover, the heel-strike events are reflected in the target gait phase with higher precision during treadmill walking than the overground walking due to the higher accuracy of force-based heel-strike detection than the marker-based method. Henceforth, the D67 network has probably learnt the heel-strike timings more precisely in treadmill walking.

3.2.2 Gait Phase Estimation in Presence of an Exoskeleton

In contrast to the previous tests, we used the joint angles computed by the exoskeleton motor encoders as the gait phase estimator inputs. The spatial performance of the D67

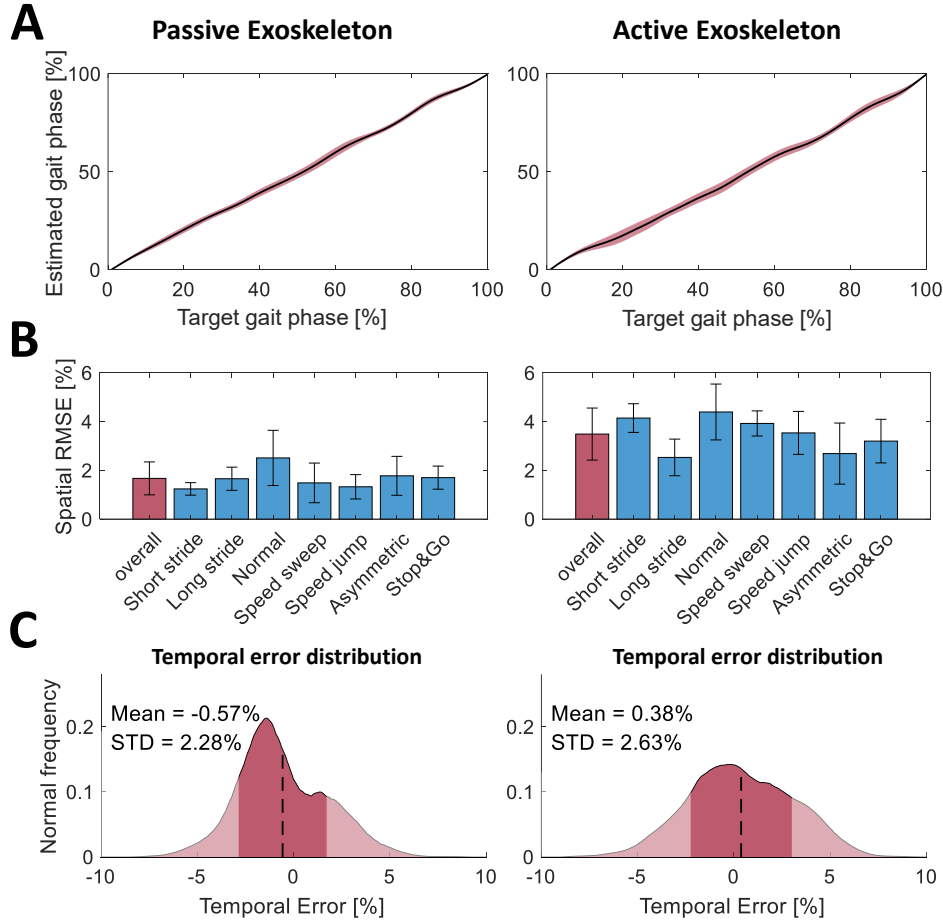


Figure 3.8: The comparison between the temporal and spatial performance of the D67 network in treadmill walking with the Passive and Active exoskeleton on participant #5. (A) overall average gait phase profiles in Passive and Active modes across experiment conditions. The shaded area shows the standard deviation. (B) the spatial performance across the experiment conditions in the Active and Passive control modes. (C) the temporal error distribution across all conditions in case of the Passive and Active exoskeletons. The mean and standard deviation of temporal errors are denoted by dashed lines and dark shaded area under the curves, respectively.

in presence of the exoskeleton in the Passive mode and Active mode in treadmill walking is shown in Fig. 3.8A,B, respectively. The D67 exhibits a slightly smaller spatial error ($1.67 \pm 0.67\%$) compared to the treadmill session without the exoskeleton. The exoskeleton regularizes gait in the Passive mode due to its passive dynamics (i.e., inertia and friction)

which causes the human lower-limb motion to be damped and, therefore, restricts the kinematic variability. In the Active mode, in contrast, the spatial error increases by almost 100% and reaches to $3.49 \pm 1.06\%$ which is still sufficiently accurate for the exoskeleton controller to provide assistance properly in all experiment conditions. The decrease in the gait phase estimation performance stems from the human-exoskeleton occasional conflicts in leading the motion since the exoskeleton assistance was not always aligned with the user intention. These conflicts emerge as excessive interaction force which to some extent distorts the gait pattern and, therefore, worsen the gait phase estimation performance. The overall estimated gait phase profile is illustrated in Fig. 3.8A. A slight distortion is noticeable in the overall gait phase both in the Passive and Active modes compared to treadmill walking without exoskeleton. This is because of the exoskeleton effect on gait pattern. The gait phase profile in the Active mode also demonstrates a higher standard deviation due to the human-exoskeleton conflicts. Furthermore, the temporal error distribution in Fig. 3.8C exhibits greater standard deviation in the Active exoskeleton mode compared to the Passive mode and no exoskeleton conditions. The Spatial distortion and the higher temporal error standard deviation issues in the Active exoskeleton mode could be alleviated by incorporating the data from walking in presence of exoskeleton in the training. This is, however, not suggested as it reduces the generalizability and robustness of the model to different exoskeleton structures and controller designs (e.g., reference trajectory and controller impedance).

3.2.3 Robustness Analysis

To compare the robustness of the trained gait phase estimators, we scrutinized the gait phase estimation in the *speed jump*, *asymmetric gait*, and *stop and go* conditions.

Abrupt speed change

We considered a single stride in the speed jump condition where the treadmill speed abruptly changes from 0.8m/s to 1.2m/s. Fig. 3.9A shows the estimated gait phase profiles averaged over all participants. While D67 and TCN network demonstrate a negligible standard deviation, the D5 exhibits an unstable gait phase estimation facing the sudden change of the treadmill speed which has led to a standard deviation more than 20%. This analysis reveals that D5 network is of no use in daily life where an exoskeleton user frequently decides to switch their gait speed. According to the overall results represented in Fig. 3.5, however, the D5 network seems to have an acceptable performance. It even seems to be a better option for practical purpose where lower computational complexity

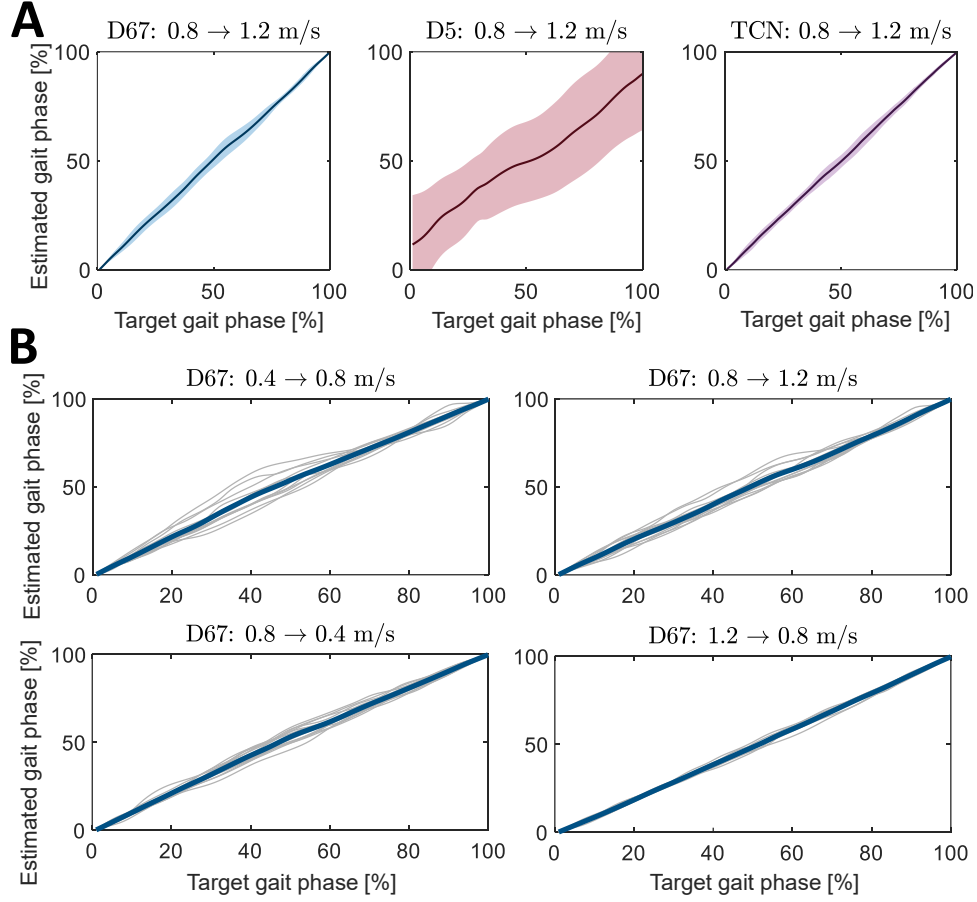


Figure 3.9: (A) Comparison of D67, D5, and [TCN](#) networks estimated gait phase mean and standard deviation (denoted by shaded area) as the treadmill speed jumped from 0.8 to 1.2m/s averaged across all participants. (B) Detailed performance of the D67 network gait phase estimation in different speed jump scenarios. Each gray line represents one of the subjects while the blue line shows the average gait phase profile.

and simple implementation is an advantage. Nevertheless, the recent robustness analysis shows that the overall performance measures such as [RMSE](#), which is widely used in the literature, are not sufficient for validating the performance of a gait phase estimator.

Robustness of D67 network is further investigated in strides when the treadmill speed has jumped back and forth between 0.4m/s, 0.8m/s, and 1.2m/s in [Fig. 3.9B](#). The estimated gait phase remained smooth for all of the participants in all cases. The highest gait phase

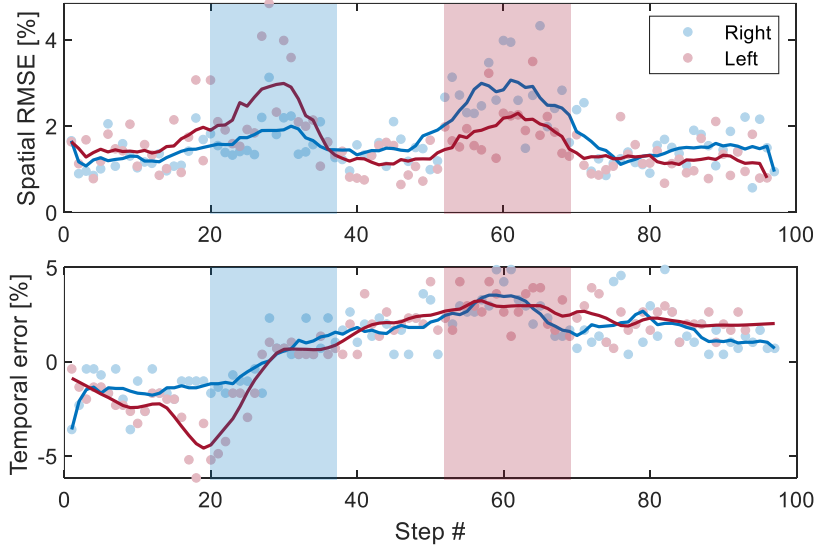


Figure 3.10: D67 spatial and temporal performance for each step of the right and left legs during asymmetric walking. The blue and red circles show the performance at each step while the corresponding curve show the smoothed performance. The intervals during which the right and left legs are severely limping are denoted by blue and red shaded areas, respectively

variation is observed in case of 0.4m/s to 0.8m/s speed increase. In general, the gait phase estimation is more variable in the case of abrupt increase in the speed rather than abrupt decrease.

Asymmetric gait

(Fig. 3.10) shows the performance of D67 in asymmetric gait condition. The spatial and temporal errors are always less than 4.81% and 6.16%, respectively, indicating stability and robustness of the estimation. As the speed difference between treadmill belts increases, the spatial error in the phase estimation of both legs increases. This is however, more stressed for the left leg during the right leg limping interval. The opposite is also valid during the left leg limping interval.

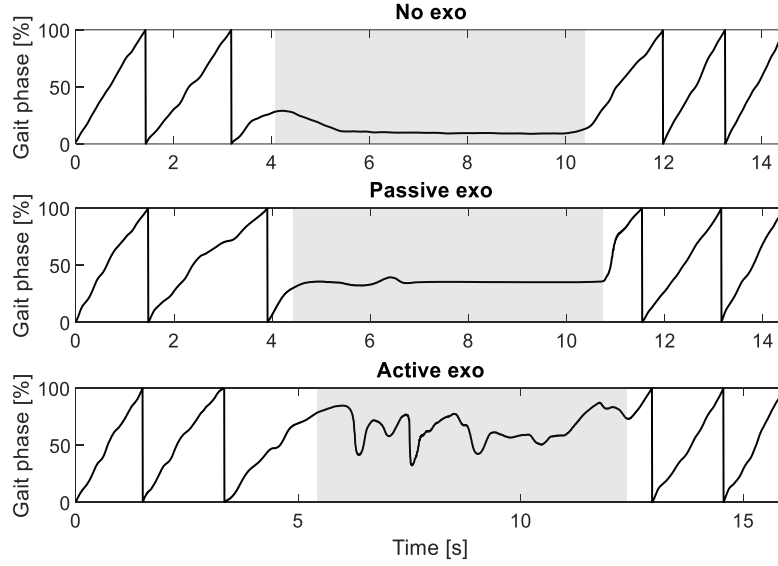


Figure 3.11: D67 gait phase estimates when the treadmill belts have stopped and start moving again for participant #5 without exoskeleton and with the exoskeleton in the Passive and Active mode, respectively. The shaded area shows the interval when the treadmill belts were fully stopped.

Stop and start

(Fig. 3.11) Shows the estimated gait phase of participant #5 with and without exoskeleton as the treadmill stops and start running again. The estimated gait phase during walking without exoskeleton and with the exoskeleton in Passive mode smoothly converges to a constant level when the treadmill stops and maintains that level until the treadmill starts running again. In the Active exoskeleton mode, the estimated gait phase slope decreases gradually as the treadmill stops. During the stop interval, however, the estimator exhibits some oscillations on the gait phase which are due to the controller design rather than the sensitivity of the gait phase estimator. With a fixed gait phase in the stop interval, the exoskeleton imposes a fixed posture and therefore, fights against the natural human motions (such as shifting the body load between legs). The resultant conflict, as mentioned earlier, disturbs the estimated gait phase.

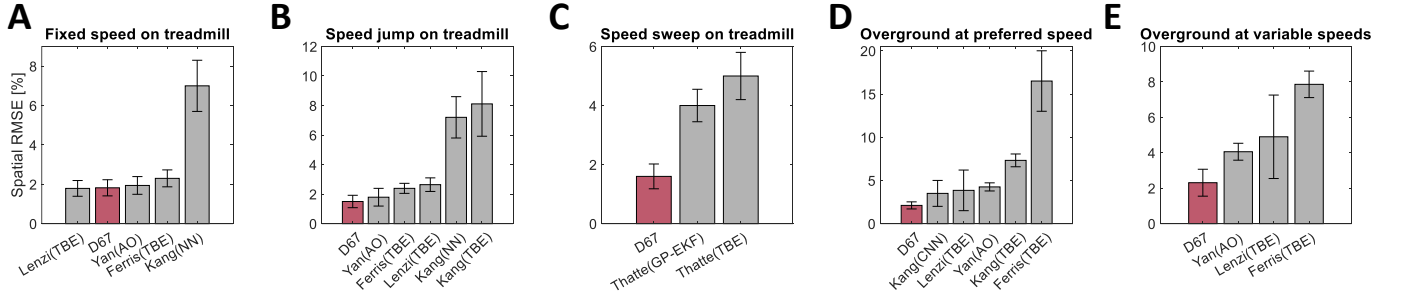


Figure 3.12: Comparison of D67 gait phase estimator performance with approaches reported in the literature for (A) fixed speed, (B) speed jumps, and (C) speed sweep in treadmill walking as well as overground walking at (D) preferred speed and (E) variable speeds.

3.2.4 Comparison with the state of the art

The performance of the D67 network is further compared to the performance of other gait phase estimators reported in literature for constant speed walking, speed jumps, and speed sweep on treadmill walking as well as overground walking at self-selected speed. We used three time-based gait phase estimators ([Time-Based gait phase Estimator \(TBE\)](#)s) developed by Lenzi et al. [68], Ferris et al. [71], and Kang et al. [54] as baselines along with the following methods compared to the D67

- **Kang(NN)**: A neural network (referred to as the independent model) trained for gait phase estimation on new participant similar to D67. The model is trained on a range of speeds between 0.6 and 1m/s, which includes steady state walking at 0.8m/s as well as speed jumps with accelerations of 0.05m/s².
- **Kang(CNN)**: Later in [55], Kang et al. trained a CNN for gait phase estimation for level ground and ramp walking as well as stair ascend and descend.
- **Yan(AO)**: An [AO](#)-based gait phase estimator developed by Yan et al. in [152] that uses foot contact sensors for phase error correction. D67 is compared to the vGRF variation of their method as it has the similar definition for gait phase. Yan(AO), Lenzi(TBE), and Ferris(TBE) methods are tested in this work during steady state walking at 0.67, 0.94, and 1.22m/s. They are additionally tested during speed jumps between the aforementioned speeds with an acceleration of 0.028m/s².
- **Thatte(Gaussian Process extended Kalman filter (GP-EKF))**: A gait phase estimator developed by Thatte et al. [135] using Gaussian Process extended Kalman

filter (GP-EKF). This method is tested on treadmill walking with a sinusoidal speed profile varying between 0.4 and 1.2m/s with a 20s period.

In fixed speed treadmill walking (Fig. 3.12A) the D67 has an RMSE of $1.82 \pm 0.41\%$ for steady state walking at 0.8m/s outperforming all the competitors but the Lenzi(TBE) which has a slightly better performance. The well-controlled gait conditions during fixed-speed treadmill walking causes lower variation in step duration and gait pattern allowing TB methods to provide accurate estimations. Besides Kang(NN), other methods also rely on heel-strike detection sensors. D67, in contrast, uses only joint angles and still provides the second best accuracy.

Fig. 3.12B shows the comparison in speed jump condition on treadmill. Kang(NN) and Kang(TBE) is tested on speed jumps between 0.6 and 1m/s with an unreported acceleration. The D67 network, with an RMSE of $1.5 \pm 0.42\%$, outperforms all approaches despite not using any contact sensors.

The comparison in speed sweep condition is illustrated in Fig. 3.12C. The D67 network resulted in RMSE of $1.6 \pm 0.42\%$ while the Thatte (GP-EKF) method obtained $4 \pm 0.55\%$ RMSE during the speed sweep experiment. For a more realistic comparison, however, both approaches should be tested on the same condition.

There is no comparable gait phase estimator presented in the literature with reported performance on asymmetric gait. As a close study, however, we also compared our method's performance with Thatte (GP-EKF) for walking with one prosthetic leg. As the other leg is intact in that study, some asymmetric features are presented in the gait. Our method resulted in RMSE of $1.69 \pm 0.33\%$ outperforming Thatte (GP-EKF) resulted in RMSE of $4 \pm 0.55\%$ RMSE. For a more realistic comparison, however, both approaches should be tested under the same conditions.

With an RMSE of $2.11 \pm 0.41\%$, the D67 outperforms the Kang(CNN) with a RMSE of $3.5 \pm 1.5\%$, the YAN(AO) with performance of $4.25 \pm 0.47\%$, and the rest of the time-based methods in overground walking with preferred speed (see Fig. 3.12D). The D67 maintains its edge over the YAN(AO) and the time-based methods in overground walking with variable speed with an average RMSE of $2.31 \pm 0.76\%$ as illustrated in Fig. 3.12E.

3.3 Conclusion

In this study, a time-delay neural network (D67) is trained using hip and knee joint angles collected from 14 participants walking on a treadmill and overground to develop an accurate and robust gait phase estimator. Several types of gait data were collected in the study

including normal gait at speeds between 0.1m/s and 1.9m/s and conditions such as long stride, short stride, asymmetric walking, stop-start, and abrupt speed changes. On average, our model’s [RMSE](#) for gait phase estimation on treadmill walking and overground walking was $1.74\pm0.23\%$, and $2.35\pm0.52\%$, respectively. The temporal analysis also revealed that D67 was able to detect heel-strike events with an average MAE of $1.70\pm0.54\%$ and $2.74\pm0.92\%$ for treadmill and overground walking, respectively. Across participants and gait conditions, spatial and temporal performance is found to be consistent. Additional analyses demonstrated the robustness of the D67 to sudden changes in walking speed, limping, changing stride length, and sudden stops or halts of walking. Furthermore, this study tested the D67’s performance with an active exoskeleton to determine its reliability in interaction with such a device. Finally the D67 model exhibits comparable or superior performance to the state-of-the-art gait phase estimators.

Our gait phase estimator is designed to enhance comfort and performance for exoskeleton-assisted walking in impaired individuals. However, the dataset was collected from healthy individuals simulating pathological gait patterns, which does not fully represent the complexity of impaired gait. Therefore, further evaluation with individuals with impaired gait is necessary to assess the robustness of our method. Future steps include incorporating pathological walking data into the training process, adding more gait conditions like stair climbing and over-ramp walking, and implementing the estimator in various assist-as-needed controllers. Additionally, leave-condition-out cross-validation can provide insights into the estimator’s performance for unseen conditions [\[133\]](#).

Chapter 4

Human–Exoskeleton Interaction Force Estimation in Indego Exoskeleton

Accurate interaction force estimation can play an important role in optimizing human–robot interaction in an exoskeleton. In this chapter, we propose a novel approach for the system identification of exoskeleton dynamics in the presence of interaction forces as a whole multibody system regardless of the gait phase or any assumption on the human–exoskeleton interaction. We hung the exoskeleton through a linear spring and excited the exoskeleton joints with chirp commands while measuring the exoskeleton–environment interaction force. Several structures of neural networks were trained to model the exoskeleton passive dynamics and estimate the interaction force. Our testing results indicated that a deep neural network with 250 neurons and 10 time delays could obtain a sufficiently accurate estimation of the interaction force, resulting in an RMSE of 1.23 on Z-normalized applied torques and an adjusted R^2 of 0.89.

4.1 Materials and Methods

4.1.1 Interaction Torque Modeling

Figure 4.1A illustrates the Indego exoskeleton and its coordination systems in the sagittal plane. This lower limb exoskeleton has seven DOFs including one rotational and two translational DOFs of the trunk (three DOFs in total) with respect to the global frame and only four active DOFs of the exoskeleton knee and hip joints of the right and left

legs. The exoskeleton also has two carbon-fiber ankle foot orthoses, which were removed from the exoskeleton due to their negligible mass. Given that the Indego exoskeleton does not have joints with off-sagittal-plane degrees of freedom (such as hip abduction and adduction DOFs) the off-sagittal dynamics of the exoskeleton during straight walking were negligible compared to its dynamics in the sagittal plane. The Indego lower-limb exoskeleton's dynamics, with actuated hips and knees, in the presence of interaction forces and torques in the sagittal plane were considered as

$$\mathbf{\Gamma}(\theta, \dot{\theta}, \ddot{\theta}, \dot{\mathbf{p}}_1, \mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{u}_{\text{act}} + \mathbf{u}_{\text{int}}, \quad (4.1)$$

where $\mathbf{p}_1 = (p_{1,x}; p_{1,y}) \in \mathbb{R}^2$ and $\theta \in \mathbb{R}$ are the exoskeleton's trunk segment position and orientation, respectively, described in the fixed global frame in the sagittal plane and ($\mathbf{q} = [q_{h,r}; q_{k,r}; q_{h,l}; q_{k,l}] \in \mathbb{R}^4$) consists of the exoskeleton right hip and knee joint angles followed by the left hip and knee joint angles. $\mathbf{u}_{\text{act}} = [\mathbf{0}_{3 \times 1}; \boldsymbol{\tau}_{\text{act}}]$ is the applied motor torques at the hip and knee joints of both legs ($\boldsymbol{\tau}_{\text{act}} \in \mathbb{R}^4$). $\mathbf{u}_{\text{int}} = [\mathbf{f}_{\text{int}}; m_{\text{int}}; \boldsymbol{\tau}_{\text{int}}]$ includes the interaction force ($\mathbf{f}_{\text{int}} \in \mathbb{R}^2$) and moment ($m_{\text{int}} \in \mathbb{R}$) applied to the exoskeleton trunk as well as the interaction torques applied to the exoskeleton joints ($\boldsymbol{\tau}_{\text{int}} \in \mathbb{R}^4$). Finally, $\mathbf{\Gamma}(\cdot)$ represents the exoskeleton passive dynamics containing the inertial forces, centrifugal and Coriolis forces, and the forces due to gravity [128]. We note that $\mathbf{p}_1$ and $\dot{\mathbf{p}}_1$ do not appear in $\mathbf{\Gamma}$ as there are no forces being applied to the trunk due to the trunk linear position ($\mathbf{p}_1$) and velocity($\dot{\mathbf{p}}_1$). Figure 4.1A provides a visual representation of the Indego lower-limb exoskeleton.

4.1.2 System Identification

To estimate the interaction forces and torques ($\mathbf{u}_{\text{int}}$), we first identified the exoskeleton passive dynamics ($\mathbf{\Gamma}$) without imposing any constraints on the system dynamics such as fixing the trunk segment. This was accomplished by hanging the exoskeleton from the ceiling by a spring with $K = 1926.4$ N/mm, with reflective markers attached to both ends (Figure 4.1B). This way, we could measure the spring deflection and consequently compute the applied interaction force ($\mathbf{f}_{\text{int}}$) accurately using Hooke's law and a motion capture system consisting of eight Vero Cameras (Vicon, UK). Note that the absence of a human participant wearing the exoskeleton during the experiment did not hinder the identification of the exoskeleton passive dynamics as the measurements of the spring force and exoskeleton joint torques were sufficient for this purpose, without imposing any constraints on the system states. The identified exoskeleton passive dynamics could then be used to estimate the human-exoskeleton interaction.

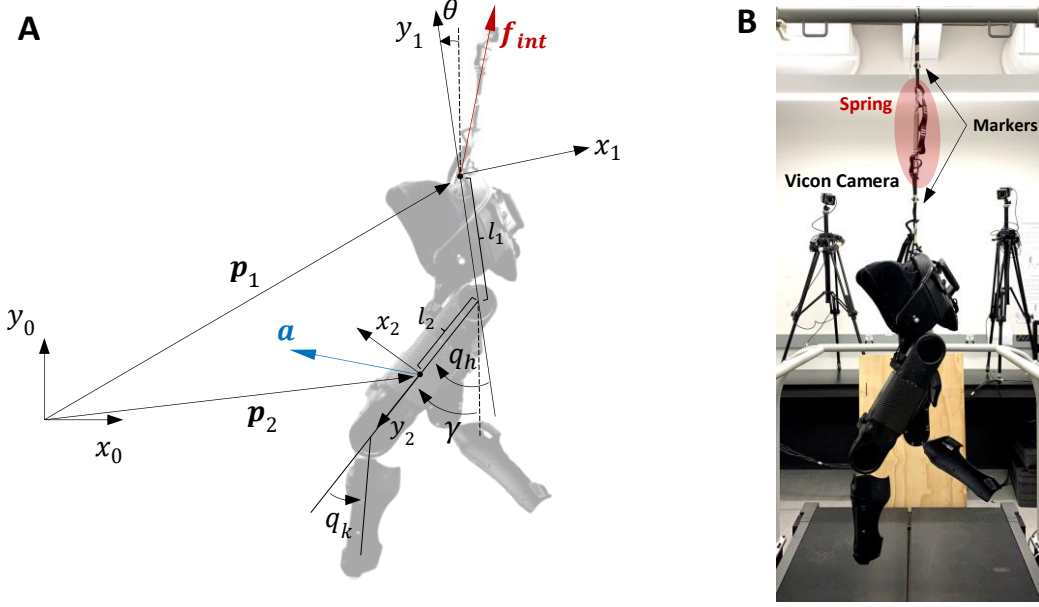


Figure 4.1: **(A)** The exoskeleton coordinates and joint angles. The global, trunk, and thigh frames are denoted by 0, 1, and 2 indices, respectively. The trunk and thigh angles with respect to gravity vector are denoted by θ and γ , respectively. q_h and q_k represent the hip and knee joint angles, respectively. p_1 and p_2 shows the position of the trunk and thigh coordinated in the global frame $((x_0, y_0))$. In blue, the acceleration vector (a) measured by the accelerometer embedded in the exoskeleton's thigh is plotted against the thigh frame. In red, we plotted the interaction force vector (f_{int}) calculated from the linear spring's deflection measured by motion capture. The distance from the trunk frame origin to the hip joint rotation axis and from there to the accelerometer location on the exoskeleton's thigh is indicated by l_1 and l_2 , and the gravity axis is illustrated by dashed lines. **(B)** The exoskeleton in hung position during data collection for dynamics identification. Joints are excited during the experiment while the exoskeleton interaction with the environment is limited to the force applied through a linear spring with reflective markers on both ends enabling us to measure the spring deflection using a motion capture system and, consequently, the applied force.

The exoskeleton joints were excited in three different scenarios each for 500 s by applying chirp command trajectories controlled by joint-level PD controllers with $k_p = 1.5$ N.m/deg and $k_d = 0.1$ N.m.s/deg for the hip and $k_p = 0.2$ N.m/deg and $k_d = 0.03$ N.m.s/deg for

the knee joint. Controller gains were obtained by trial and error to achieve a maximum tracking error of less than 10 degrees for the hip and 5 degrees for the knee joint during the experiment. The chirp commands had unique initial and final frequencies to prevent phase lock between joints (see Figure 4.2). The chirp signals were designed to cover at least 80% of each joint range of motion with frequencies between 0.2 to 0.9 Hz covering the speed ranges below 1.4 m/s for healthy individuals [86]. The spring force measurement, as well as the exoskeleton data consisted of its joint angles ($\mathbf{q}$), angular velocity ($\dot{\mathbf{q}}$), the angle of each thigh with respect to gravity ($\gamma \in \mathbb{R}$), the linear acceleration of each thigh ($\mathbf{a} = [a_x; a_y] \in \mathbb{R}^2$), and the applied joint torques ($\boldsymbol{\tau}_{\text{act}}$) were acquired at 200Hz. By choosing different upchirp and downchirp rates for the command trajectories to each joint, we applied three different patterns for the interaction forces to the exoskeleton trunk. During the first scenario (training dataset), the right hip and left knee frequencies upchirped from 0.2 Hz to 0.9 Hz, while the left hip and right knee frequencies downchirped from 0.9 Hz to 0.2 Hz. All joints in the second scenario (validation) upchirped from 0.2 Hz to 0.9 Hz. Finally, in the last scenario (test), the joints on the right leg upchirped from 0.2 to 0.9 Hz while those on the left leg downchirped from 0.9 to 0.2 Hz. In all these cases, the frequency sweep rate for the upchirping or downchirping joints were selected slightly different to prevent phase locking between joints (Figure 4.2).

According to Equation (4.1), we then computed the trunk orientation (θ) and its derivative in addition to its linear acceleration ($\ddot{\mathbf{p}}_1$) to train a data-driven model for the estimation of exoskeleton passive dynamics (Γ). Even though this information was not directly included in the exoskeleton measurements, they were obtained using either of the thigh's linear accelerometer measurements ($\mathbf{a}$) or through obtaining its angle (γ) with respect to the gravity vector (g). The trunk orientation was then computed using the angle (γ) and the corresponding hip joint angle (the angle between the thigh and the upper segment) measured using the motor encoders. Therefore, we drop the leg index hereafter. According to Figure 4.1A, we could simply obtain the trunk orientation as

$$\theta = q_h - \gamma. \quad (4.2)$$

To obtain $\ddot{\mathbf{p}}_1$, we first mapped the thigh acceleration ($\mathbf{a}$) from the thigh coordinate to the global coordinate frame. As the thigh coordinate frame ((x_2, y_2)) rotated clockwise by $\pi - \gamma$ rad compared to the global frame ((x_0, y_0)), the linear acceleration measured in the thigh frame ($\mathbf{a}$) could be mapped to the global frame as

$$\ddot{\mathbf{p}}_2 = R_2^0(\gamma)\mathbf{a} = \begin{bmatrix} \cos(\pi - \gamma) & -\sin(\pi - \gamma) \\ \sin(\pi - \gamma) & \cos(\pi - \gamma) \end{bmatrix} \mathbf{a} = \begin{bmatrix} -\cos(\gamma) & -\sin(\gamma) \\ \sin(\gamma) & -\cos(\gamma) \end{bmatrix} \mathbf{a}. \quad (4.3)$$

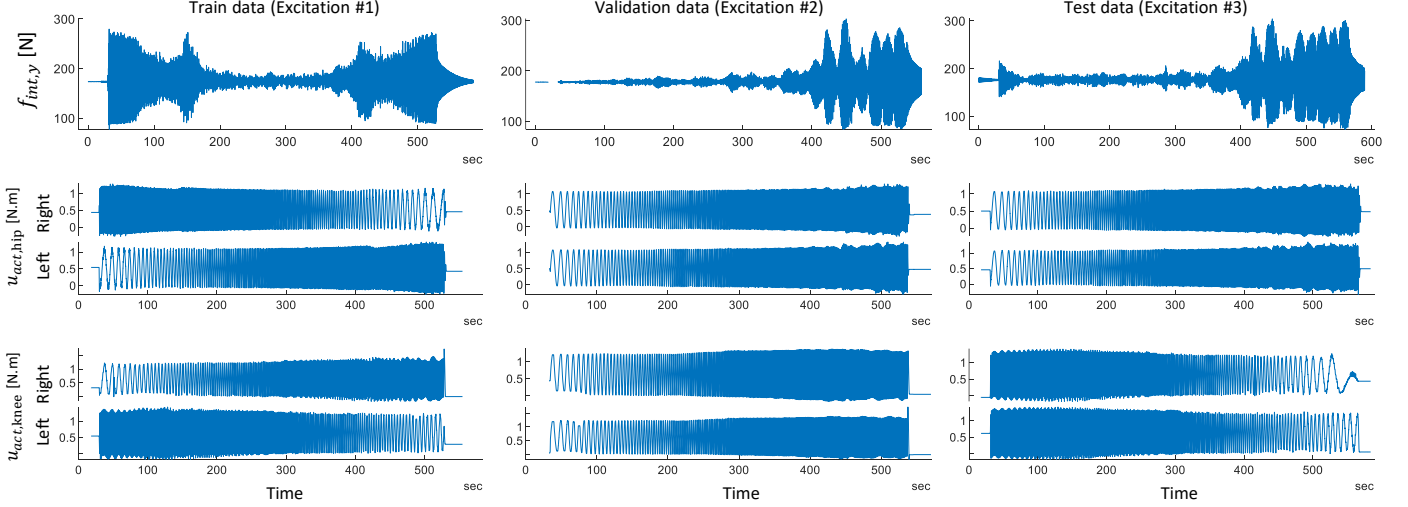


Figure 4.2: The hip and knee excitation torques applied to the left and right exoskeleton legs, as well as the interaction force on the y axis. During the generation of each of the training, validation, and test datasets, exoskeleton joints were activated with unique and different chirp commands resulting in different exoskeleton–environment interaction profiles.

Moreover, the following equation holds between the origin of the trunk frame and the accelerometer position with respect to the global frame ($\mathbf{p}_2 = (P_{2,x}; p_{2,y})$)

$$\mathbf{p}_1 = \begin{pmatrix} p_{2,x} + l_2 \sin(\gamma) - l_1 \sin(\theta) \\ p_{2,y} + l_2 \cos(\gamma) + l_1 \cos(\theta) \end{pmatrix}. \quad (4.4)$$

Taking the second derivative from the above equation and substituting Equation (4.3), we obtain

$$\ddot{\mathbf{p}}_1 = \begin{pmatrix} l_2 s_\gamma \dot{\gamma}^2 + l_1 s_\theta \dot{\theta}^2 - c_\gamma a_x - s_\gamma a_y + \ddot{\gamma} c_\gamma l_2 - c_\theta l_1 \ddot{\theta} \\ -c_\gamma l_2 \dot{\gamma}^2 - c_\theta l_1 \dot{\theta}^2 - c_\gamma a_x - s_\gamma a_y - \ddot{\gamma} l_2 s_\gamma - l_1 s_\theta \ddot{\theta} \end{pmatrix}, \quad (4.5)$$

where c_x and s_x are shorthand versions of $\sin(x)$ and $\cos(x)$, respectively. According to Equations (4.2) and (4.5), both θ and its derivatives, as well as $\ddot{\mathbf{p}}_1$, could be obtained as a function of the exoskeleton joint angles ($\mathbf{q}$), thigh accelerations ($\mathbf{a}$), thigh orientation with respect to gravity (γ), and their derivatives. In other words, we have

$$[\theta; \dot{\theta}; \ddot{\theta}; \ddot{\mathbf{p}}_1] = h(\gamma, \dot{\gamma}, \ddot{\gamma}, \mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, \mathbf{a}). \quad (4.6)$$

Henceforth, without loss of generality, we can consider Γ as only a function of the exoskeleton measurements and rewrite Equation (4.1) as

$$\Gamma(\gamma, \dot{\gamma}, \ddot{\gamma}, \mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, \mathbf{a}) = \mathbf{u}_{\text{act}} + \mathbf{u}_{\text{int}}. \quad (4.7)$$

Therefore, we can use the thigh angle with respect to the gravity vector and its linear acceleration instead of the position and orientation of trunk segment to identify Equation (4.1). Moreover, we defined the origin of the exoskeleton's trunk frame exactly at the point where the spring force was applied (Figure 4.1). This allowed us to consider $m_{\text{int}} = 0$. Equation (4.1) can thus be further simplified as

$$\Gamma(\mathbf{x}) = \mathbf{y}, \quad (4.8)$$

where $\mathbf{x} = [\gamma; \dot{\gamma}; \ddot{\gamma}; \mathbf{q}; \dot{\mathbf{q}}; \ddot{\mathbf{q}}; \mathbf{a}] \in \mathbb{R}^{17}$ and $\mathbf{y} = [\mathbf{f}_{\text{int}}; 0; \boldsymbol{\tau}_{\text{act}}] \in \mathbb{R}^7$.

Various time-delay ANNs [142] with a tanh activation function (Figure 4.3B) were trained on the training dataset to learn the exoskeleton's passive dynamics ($\hat{\Gamma}(\mathbf{x}) = \hat{\mathbf{y}}$) by minimizing the root mean squared error (RMSE) between the Z-score normalized measured ($\mathbf{y}$) and estimated ($\hat{\mathbf{y}}$) forces and torques (Figure 4.3A) using the scaled conjugate gradient backpropagation algorithm [89]. The training was stopped when 10 consecutive iterations did not improve the performance of the ANN on the validation dataset. Different combinations of network structure (ranging from a single hidden layer with 10 neurons to three hidden layers with 250 neurons in total), number of input delays (ranging from 0 to 50 samples), and L^2 weight regularization factors (ranging from 0 to 0.5) were evaluated according to (Figure 4.4A), by training each network five times and computing their mean performance on the validation dataset to compare networks and to obtain the best architecture.

4.1.3 Experimental Estimation of Human–Exoskeleton Interaction Torque

We estimated the human–exoskeleton interaction torques by conducting experiments on three able-bodied participants. Interaction torques were estimated in real time using the exoskeleton measurements fed to the N9 network implemented on a real-time kernel using MATLAB Simulink Desktop Real-time toolbox running at 200 Hz. The participants included two 22-year-old males with heights of 180 cm and 182 cm, and body masses of 82 kg and 90 kg, respectively, and a 24-year-old female with a height of 174 cm and body mass of 68 kg. They walked on a treadmill at slow (0.4 m/s), medium (0.6 m/s), and fast (0.8

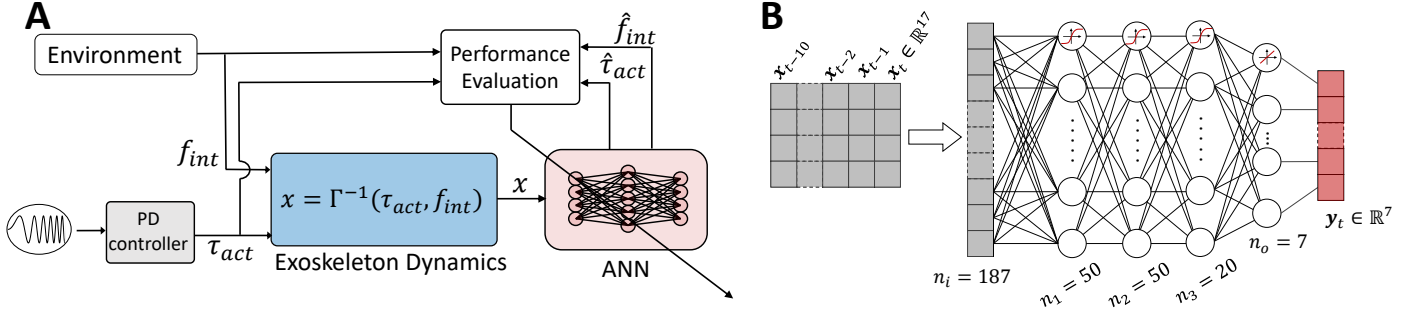


Figure 4.3: **(A)** Block diagram of the exoskeleton dynamic identification experiment. The interaction force (f_{int}) is applied to the exoskeleton through a linear spring through which the exoskeleton is hung. Exoskeleton joints are controlled by chirp position commands using PD controllers applying the excitation torques (τ_{act}) to the exoskeleton. Measurements of the exoskeleton (x), containing joint angles and their derivatives as well as the thigh angle with respect to the gravity vector and its linear acceleration, are fed to a neural network for the estimation of the interaction force ($\hat{f}_{int}$) and motor torques ($\hat{\tau}_{act}$), which are then compared to their actual values. The estimation error is then used to update the neural network weights to improve its estimation accuracy. **(B)** Structure of a time-delay neural network with 10 input delays and 3 hidden layers with 50, 50, and 20 neurons, respectively, with a *tanh* activation function.

m/s) speeds while wearing a passive exoskeleton. All participants had no known musculoskeletal impairments and provided informed consent prior to the experiment. The study protocol and procedures were approved by the University of Waterloo Clinical Research Ethics Committee (ORE#41794) and conformed to the Declaration of Helsinki.

Knowing the exoskeleton passive dynamics, we could estimate the human–exoskeleton interaction forces and torques using Equation (4.1) as

$$\mathbf{u}_{int} = \hat{\mathbf{\Gamma}}(\mathbf{x}) - \mathbf{u}_{act} = \hat{\mathbf{y}} - \mathbf{u}_{act}. \quad (4.9)$$

In this case, since the exoskeleton motors applied no torques ($\mathbf{u}_{act} = 0$), the estimated interaction torques were obtained as $\mathbf{u}_{int} = \hat{\mathbf{\Gamma}}$.

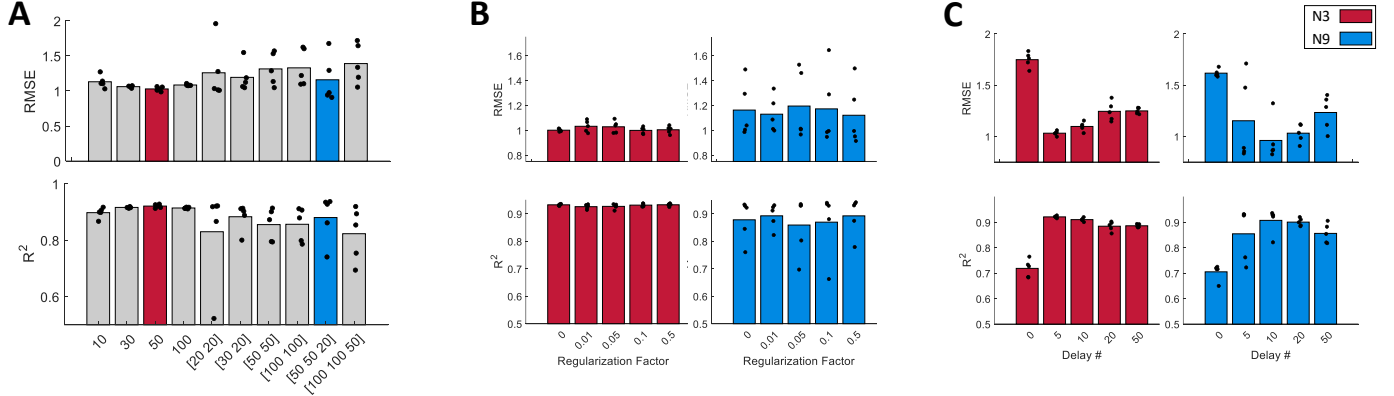


Figure 4.4: (A) Validation performance of ANNs with 10 different structures in terms of RMSE and adjusted R^2 computed on the z-normalized data. The training procedure was repeated 5 times for each structure to study the sensitivity of the training procedure to the network's initial weight for each structure. Each validation performance is denoted by a black dot while the average performance is denoted by bars. The training was conducted with 5 input delays and no regularization. N3 (denoted by red) and N9 (denoted by blue) demonstrated a better performance compared to the other networks. N9, however, exhibited more variability across training repetitions. Those networks were selected for further analysis to investigate the effect of regularization factor and the number of input delays. (B) Comparison of N3 and N9 performance across different selections of regularization factors. The variation of the N9 performance across training repetitions is unaffected by regularization. (C) Effect of the number of input delays on the N3 and N9 networks' performance. N3 has the best performance with 5 input delays while N9 reaches the best performance at 10 input delays.

4.2 Results and Discussion

4.2.1 Tuning the Network Structure and Hyperparameters

To tune the network structure and complexity, we trained ten networks with complexities ranging from a single hidden layer with 10 neurons up to a network with three hidden layers with 250 neurons in total. Figure 4.4A shows the average RMSE and the coefficient of determination (R^2) computed using each of the trained networks on the validation datasets. The training procedure was repeated five times for each network to account for the randomness of the training process without a regularization coefficient and with input delays equal to five. Our results indicated that the average test performance dropped as

the network complexity increased. This was indicated by the increase in the average RMSE and the decrease in the average adjusted R^2 after N3 (the third network denoted by red in Figure 4.4A), which resulted in one of the best performance results consistently in all five training trials (RMSE = 1.03 R^2 = 0.92). On the other hand, the RMSE and R^2 variations on the validation dataset also increased with the network complexity. This can be explained by the association between the networks' expressiveness and overfitting. N9 (the ninth network denoted by blue in the same graph), for example, obtained one of the best validation performance results among all networks three out of five times. To further improve the results, the training procedure was repeated for N3 and N9 with regularization coefficients ranging from 0 to 0.5 and with different numbers of input delays ranging from 0 to 50 samples equal to 0–250 ms.

Figure 4.4B investigates the effect of the regularization coefficient on N3 and N9's performance results, indicating that increasing the regularization coefficient improved neither the network performance in the case of N3 nor the consistency of the validation results in case of N9. The number of input delays, on the contrary, showed to be effective in enhancing both networks' performance. According to Equation (4.8), providing ANNs with histories of $\mathbf{x}$ would not be effective as $\mathbf{\Gamma}$ is solely a function of $\mathbf{x}$. However, the best performance for N3 was obtained with 5 input delays (RMSE = 0.99 and R^2 = 0.92), while N9's best performance was obtained with 10 input delays (RMSE = 0.82 and R^2 = 0.93). The underlying reason was that by adding input delays, the ANNs could learn to smooth the input data and therefore become less sensitive to the input noise. The more flexible structure of N9 enabled it to benefit from the additional information embedded in the input history, while N3's capacity became saturated with more than five input delays, and therefore, N9 was able to reach a less biased performance. Hence, we chose N9 consisting of three hidden layers each with 50, 50, and 20 neurons, respectively, with 10 input delays, for the estimation of the exoskeleton dynamics.

4.2.2 N9 Performance on Test Dataset

The overall RMSE of N9 on the test dataset was 1.23 and R^2 = 0.89. Figure 4.5 shows the test performance of N9 for each output channel. The relative error was computed by normalizing the estimation error over the maximum range of each output channel. For example, according to Figure 4.2, the range of $f_{int,y}$ was about 200 N. In that case, 1% of relative error means 2 N of force estimation error. The trained network exhibited an accurate estimation of the applied exoskeleton joint torques with a coefficient of determination greater than 0.9. The knee torque estimation was slightly more biased compared to the hip due to the more pronounced static friction at the knee. Particularly, at lower

speeds, the larger mass (4.7 kg) of the thigh segment dominated the static friction of the motor gears at the hip joint, resulting in a more predictable dynamical behavior. The light weight of the shank segments, in contrast, was negligible (0.6 kg) compared to the static friction and motor backlash, causing a greater estimation bias at the knee. This was evident from the dead zone-like behavior emerging in the $y-\hat{y}$ graphs for the knees. At the higher speeds when static friction was dominated by inertial and damping torques, the knee torque estimations were more accurate than the hip joint due to its smaller moment of inertia leading to a higher coefficient of determination at the knee joint. The RMSE value for the interaction forces was higher than the joint torques. Simplifying the exoskeleton dynamics into the sagittal plane was the main reason behind this, as our model could not represent the applied interaction force to the exoskeleton trunk in the z direction. The external forces were also estimated with an RMSE smaller than 1.6 with a negligible bias ($ME < 0.2\%$).

4.2.3 Human–Exoskeleton Interaction Torque Estimation

The estimated interaction torques at the hip and knee joints of the right leg are presented for three participants walking on a treadmill at slow, medium, and fast speeds in Figure 4.6. The estimated torques are plotted against the estimated gait phase [122], i.e., a gait-cycle-based monotonic measure often defined based on gait events such as heel strike and used to elucidate the evolution of the gait cycle [146]. The results showed a similar behavior in the estimated interaction torques at both joints regardless of the participant and walking speed. As expected, the magnitude of the interaction torques at both joints increased as the walking speed increased. At the knee joint (Figure 4.6B), a large peak during the late swing and early stance phase (about 10% of the gait cycle) indicated that the interaction torque was in favor of a knee flexion for damping the knee ballistic swing before the heel strike and stabilizing the knee after the heel strike. In the late stance and early swing phases (approximately 60% of the gait cycle), a negative interaction torque peak was in the direction of a knee extension, which was required to throw the exoskeleton shank segment forward during the swing phase.

At the hip joint (Figure 4.6A), a relatively large peak occurred during the late stance phase, indicating that the user torque tended to flex the exoskeleton hip joint. Similarly, a less pronounced and unexpected peak was also exhibited in the early stance phase. This was surprising since the hip joint typically extends during this phase, leading to an anticipated negative interaction torque. To better understand this observation, it was necessary to consider the left hip gait phase and its interaction torque. During the early stance phase

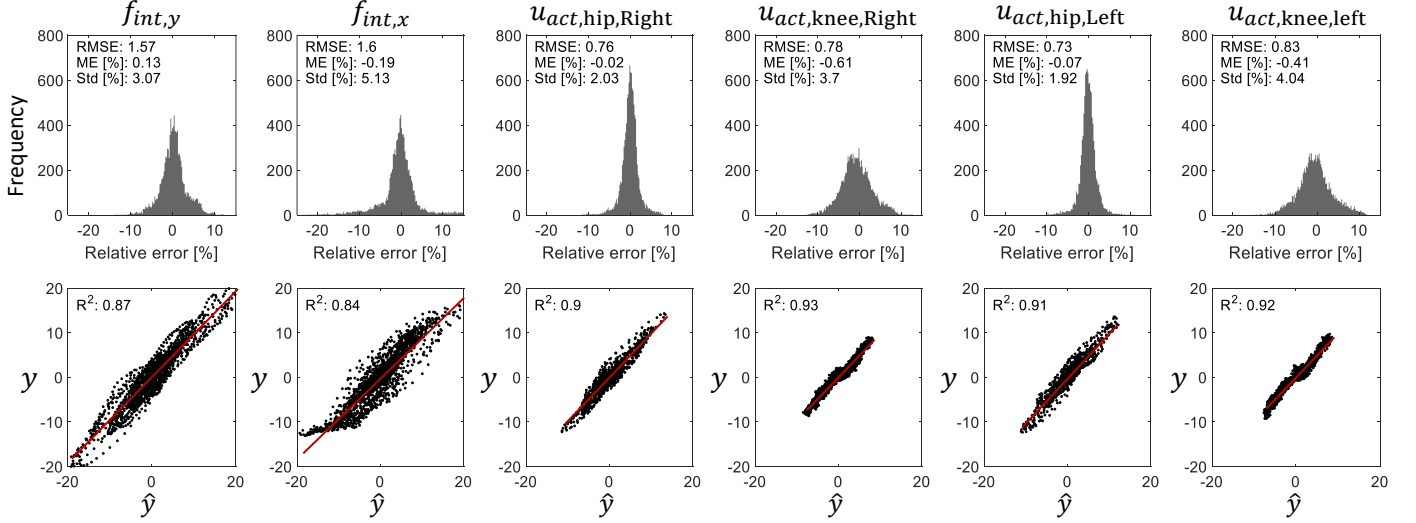


Figure 4.5: The test performance of N9 for each output channel. In the top row, the distribution of the estimation error of external force or joint applied torques relative to their peak-to-peak range is depicted. Interaction forces in the y and x direction exhibit a higher estimation error compared to those of the exoskeleton active joints. Applied torques to the hip joints, in particular, are estimated with a higher accuracy and smaller standard deviation. Even though knee joint applied torques are estimated with similarly small errors (small bias), they show a higher standard deviation associated to the more prominent role of static friction. The bottom row shows the correlation between the measured data and the N9 estimation for each output channel. The estimated outputs have a relatively lower coefficient of determination in case of interaction forces, while they show $R^2 > 0.9$ for the active joints of the exoskeleton.

of the right leg, the left leg was in its early swing phase, applying a large positive interaction torque to the left joints of the exoskeleton. Since the trunk segment of the exoskeleton was shared between the right and left thigh segments, the isolation of those two interaction torques was not fully possible, leading to a leakage of interaction torques between the left and right hip joints of the exoskeleton. Consequently, the large positive flexion torque of the left hip manifested itself in the estimated interaction torque at the right hip, and vice versa when the left leg was in the early stance phase.

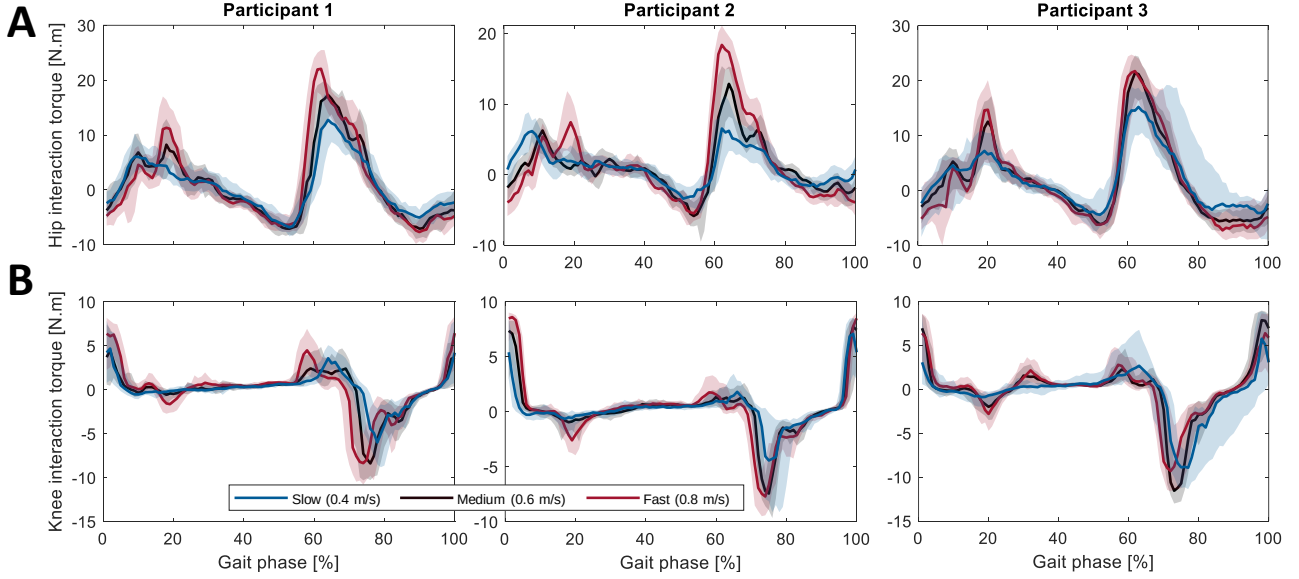


Figure 4.6: The estimated interaction torques at (A) the hip and (B) the knee joints of the right leg for three participants walking at different speeds (ranging from 0.4 m/s to 0.8 m/s) are shown. The values represent the average across different steps. The solid lines represent the median of the estimated interaction torque, while the shaded area represents the torques that fall within the 5th to 95th percentile. Positive torque values are in favor of joint flexion while negative values are in favor of joint extension.

4.3 Conclusions

The dynamics of a lower-body exoskeleton were identified and used for the estimation of the human–exoskeleton interaction torques. An exoskeleton was hung using a linear spring allowing us to measure the exoskeleton–environment interaction forces by motion capture. Meanwhile, exoskeleton joints were excited with different chirp commands designed to cover the range of motion of all joints in three scenarios, each used either for the training, validation, or test of the data-driven model. Various time-delay ANNs were trained and validated on the collected datasets and the network structure, the number of input delays, and regularization factors were tuned according to their validation performance. Testing results indicated an accurate performance of the exoskeleton joint torque estimation (RMSE < 0.85 , ME $< 0.6\%$, and $R^2 > 0.9$) as well as an acceptable performance of the interaction force estimation (RMSE < 1.6 , $R^2 > 0.84$). One of the challenges of the presented method was the redundancy between the estimated interaction torques at the left and right hips

due to sharing the trunk segment. Modeling the exoskeleton motion in the sagittal plane is another limitation of this work. Even though a high accuracy in the joint torque estimation was obtained, with more accurate modeling of the exoskeleton in 3D space, we could model the interaction forces applied to the exoskeleton better. Developing a driftless trunk orientation estimation method is another challenge in this regard, which is required for monitoring the orientation of the exoskeleton trunk in 3D space continuously. Despite these challenges, this direction will have implications for building a data-driven ground reaction force estimator in our future work or using force-plate-free predictions of joint net torques [23]. Our next step, however, is to integrate the identified exoskeleton dynamics in our adaptive trajectory and feed-forward controllers [94, 124], which were only tested in simulation due to the lack of ability to estimate the human–exoskeleton interaction torques.

4.4 Supplementary Material: Model-based Estimation of Indego Exoskeleton

4.4.1 Indego Exoskeleton

Exoskeleton dynamics identification is required for estimation of interaction force as well as dynamic compensation. In this section, I focus on the identification problem of Indego exoskeleton (Fig. 4.7.A). Indego is a lower limb exoskeleton with two degrees of freedom for hip and knee joints of each leg driven by brushless DC motors. The exoskeleton has also built-in carbon fiber ankle-foot passive orthoses that provide ankle stability and transmit the weight of the exoskeleton to the ground. Therefore, the dynamical equations of Indego during walking are explained either by a 4-DOF serial or parallel manipulator in the single or double support phases, respectively.

Two modes of current control (torque control) and impedance control are available for each motor. Sensory information includes each motor’s position, velocity, current, and temperature as well as the IMU data included in each upper leg segment. A real-time controller implemented in Matlab Simulink receives sensory information and sends control commands using a CAN bus interface with a refresh rate of 200Hz.

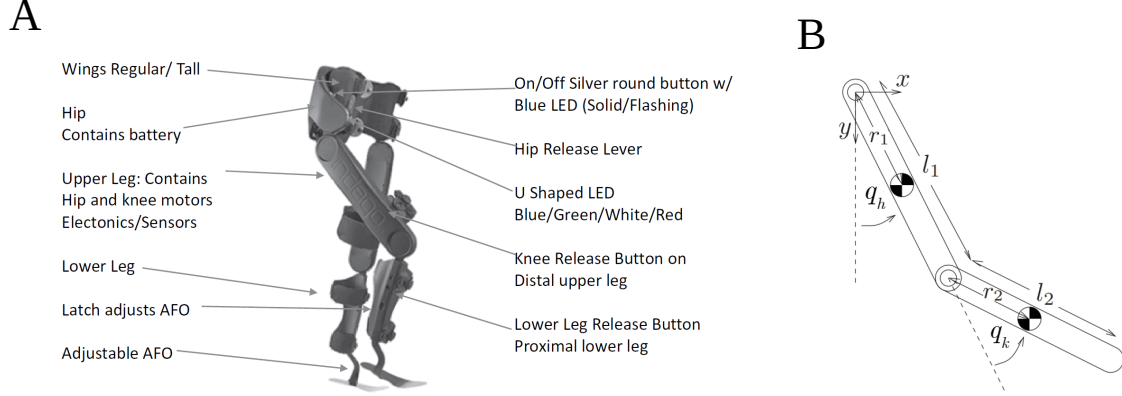


Figure 4.7: (A) Indego exoskeleton consisting of 5 segments and actuated by 4 motors at the right and left legs, hip and knee joints and passive ankle orthoses [134]. (B) Swing leg modeling as a two-link manipulator. l_1 and l_2 are the length of upper and lower leg, respectively. r_1 and r_2 are also the location of center of mass on each segment.

4.4.2 System Identification Objectives

Interaction Torque Estimation

The first objective of system identification is to estimate the interaction force between the user and the exoskeleton. In this regard, the estimation of the exoskeleton joint torques is needed ($\vec{\tau}_{\text{exo}}$) to compute the interaction torques as $\vec{\tau}_{\text{interaction}} = \vec{\tau}_{\text{applied}} - \vec{\tau}_{\text{exo}}$ where the applied torque ($\vec{\tau}_{\text{applied}}$) is the vector of motor applied torques. As a preliminary study, I focused on the estimation of exoskeleton torque in the swing leg assuming that the swing leg is governed by the dynamics of a tow-link manipulator in the swing phase (Fig. 4.7.B). Training data ($\vec{\tau}_{\text{exo}}$, $\vec{q}$, $\dot{\vec{q}}$ and $\ddot{\vec{q}}$) was collected while the upper leg of the exoskeleton was fixed and independent sine torques were applied to both knee and hip joints. To excite the system as much as possible, the frequency of the applied torque to both joints varied between 0 to 1 Hz independently. The amplitude of applied torque to each joint was also modulated to achieve the highest possible range of motion at each joint. The system identification problem is then formulated as:

$$\vec{w}^* = \arg \min_{\vec{w}} (\vec{\tau}_{\text{exo}} - \hat{\vec{\tau}}_{\text{exo}})^T (\vec{\tau}_{\text{exo}} - \hat{\vec{\tau}}_{\text{exo}}) \quad , \quad \hat{\vec{\tau}}_{\text{exo}} = f(\vec{q}, \dot{\vec{q}}, \ddot{\vec{q}}, \vec{w}) \quad (4.10)$$

where $\hat{\vec{\tau}}_{\text{exo}} = f(\vec{q}, \dot{\vec{q}}, \ddot{\vec{q}}, \vec{w})$ is the parametric model and $\vec{w}$ is the vector of model parameters. f was determined using dynamical model of two-link manipulator (Fig. 4.7.B) as the

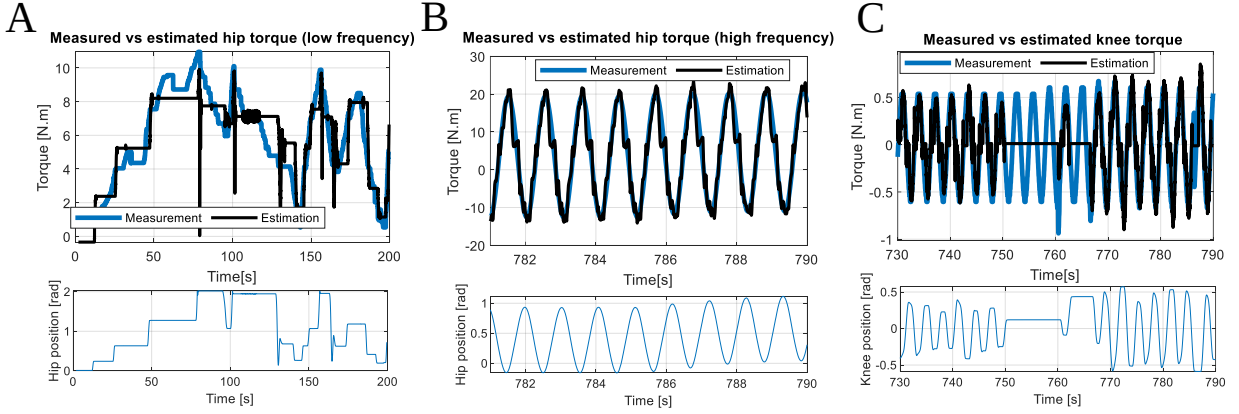


Figure 4.8: Single joint identification of hip and knee joints. (A) Hip joint estimated torque, measured torque, and position in low frequency where the static friction effect is dominant. (B) Hip joint estimated torque, measured torque, and position in high frequency where the static friction effect is diminished. (C) Knee joint torque. estimation at high frequency. The effect of static friction is still dominant even in high frequencies.

parametric model [91, pp. 165]:

$$\begin{aligned}
 \hat{\tau}_{\text{exo},h} &= w_1 \ddot{q}_h + w_2 \ddot{q}_k + w_3 (2\ddot{q}_h c_k + \ddot{q}_2 c_k - s_2 \dot{q}_k (2\dot{q}_h + \dot{q}_k)) + w_4 s_h + w_5 s_{h+k} \\
 &\quad + w_6 \dot{q}_h + w_7 \text{sgn}(\dot{q}_h) \\
 \hat{\tau}_{\text{exo},k} &= w_2 (\ddot{q}_h + \ddot{q}_k) + w_3 (\ddot{q}_1 c_k + \dot{q}_1^2 s_k) + w_5 s_{h+k} + w_8 \dot{q}_k + w_9 \text{sgn}(\dot{q}_k)
 \end{aligned} \tag{4.11}$$

where $w_1, \dots, w_5$ are functions of each segment's mass, moment of inertia, and center of mass position, while $w_6, \dots, w_9$ are friction coefficients. In the above equations, s and c are shorthand for $\sin(\cdot)$ and $\cos(\cdot)$ functions. For example $s_{h+k} = \sin(q_h + q_k)$. Eq. 4.11 is a linear model ($f = \phi^T w$) in terms of w where $\phi_{9 \times 2}$ is the matrix of basis functions.

Fitting the above parametric model to the collected data, nevertheless, did not lead to an acceptable performance, particularly at knee joint dynamic identification ($\text{MSE}_{\text{total}} = 4.45$ N.m, $\text{MSE}_{\text{hip}} = 2.38$ N.m, $\text{MSE}_{\text{knee}} = 2.06$ N.m, $R_{\text{hip}} = 0.92$, and $R_{\text{knee}} = 0.94$, where MSE is the mean square error and R is the Pearson correlation coefficient between measured and estimated torques). The underlying reason is the unmodeled dynamics and measurement noise. This is more observable in identification of the knee joint and lower leg since it is very light (0.6 Kg) compared to its upper leg segment (4.17 Kg). Therefore, unmodeled dynamics such as static friction and measurement noises are more pronounced in the knee torque measurement than the hip joint.

Dynamic Compensation

Dynamic compensation is required for feedback linearization of the exoskeleton dynamics. Even in the case of using an independent joint control method, gravity and friction compensation enhances the controller performance as well as the user comfort given that the exoskeleton's upper leg segments are heavy (4.17 Kg) and its joints have considerable amount of static friction. In this regard, I need to identify the Mass, Centrifugal and Coriolis matrices, and Gravity vector.

I approached this problem by identification of each segment's mass, moment of inertia, location of the center of mass, and friction parameters. Having these parameters enables us to compute dynamical equations of the system in both serial and parallel configurations. furthermore, data collection and model fitting in a single joint identification problem is more straightforward than a multi-joint one. This is vital in case of Indego dynamic identification because fixing the exoskeleton lower leg segment and exciting other joints simultaneously is a challenging task since the lower leg segment is not designed to tolerate the exoskeleton weight without a human in it.

Dynamical model of a 1-DOF rotary link yields:

$$(I + ml^2) \ddot{q} + mgl \sin(q) + F_{\text{friction}} = \tau \quad (4.12)$$

where m , l , and I are the mass, location of the center of mass on the link, and the moment of the inertia about the center of mass, respectively. F_{friction} stands for Coulomb, viscous, and static friction [109, 141]:

$$F_{\text{friction}} = \begin{cases} C_n \text{sgn}(\dot{q}) + b_n \dot{q} & \dot{q} < -\Delta v \\ \max(D_n, F_a) & -\Delta v < \dot{q} < 0 \\ \min(D_p, F_a) & 0 < \dot{q} < \Delta v \\ C_p \text{sgn}(\dot{q}) + b_p \dot{q} & \dot{q} > \Delta v \end{cases} \quad (4.13)$$

where C_p and C_n are the positive and negative values of the Coulomb friction; b_p and b_n are the positive and negative values of the viscous friction; D_p and D_n are the positive and negative values of the static friction; Δv is the value below which the velocity is considered to be zero, and; F_a is the sum of non-frictional forces being applied to the system. In order to compare the effect of consideration of static friction force in the model, the dynamical model was fitted in Eq. 4.12 once with F_{friction} computed from Eq. 4.13 and once with $F_{\text{friction}} = C \text{sgn}(\dot{q}) + b \dot{q}$ where C and b are the Coulomb and viscous friction coefficients in both directions. The optimization problem is solved using constrained nonlinear optimization toolbox in Matlab (fmincon). All the parameters were constrained to be positive. D_n ,

Table 4.1: Upper leg and hip joint identification with and without consideration of static friction effect

Static friction	MSE		Parameters								
	Actual	Practical	$I + ml^2$	mgl	C_n	C_p	b_n	b_p	D_n	D_p	Δv
Yes	2.11	2.92	0.63	7.37	0.37	0.5	0.66	0.56	3.97	4.23	0.002
No	2.82		0.64	7.81	0.43		0.59		-	-	-
Nominal value	-		0.2186	8.18	-	-	-	-	-	-	-

Table 4.2: Lower leg and knee joint identification with and without consideration of static friction effect

Static friction	MSE		Parameters								
	Actual	Practical	$I + ml^2$	mgl	C_n	C_p	b_n	b_p	D_n	D_p	Δv
Yes	0.06	0.39	0.034	0.7	0.25	0.26	0.16	0.14	2	2	0.005
No	0.35		0.047	1.01	0.27		0.16		-	-	-
Nominal value	-		0.05	1.47	-	-	-	-	-	-	-

D_p , and Δv were also constrained to be smaller than 5, 5, and 0.01 for hip and 2, 2, and 0.005 for knee, respectively.

Accurate computation of F_a is impossible in practice due to the interaction force between exoskeleton and the user. Therefore, in addition to the actual MSE, the practical MSE is also reported for the system identification in case of considering static friction. Practical MSE is computed with $F_{\text{friction}} = 0$ when $|\dot{q}| < \Delta v$. Tab. 4.1 shows the result of system identification at hip joint. According to the table, the addition of static friction does not improve the practical performance of model fitting. Comparing the MSE with the amplitude of the maximum applied torque to the hip joint (in Fig. 4.8.B), we can conclude that both methods have acceptable fitting performances. The dynamical model without static friction is, however, preferred due to its simplicity and slightly better performance. The performance of dynamic identification is depicted in Fig. 4.8 for the low and high frequencies of the applied torque. According to these figures, the effect of static friction is mostly dominant in lower frequencies. This effect is reduced in relatively higher frequencies which leads to better performance in dynamic identification.

In contrast to the hip joint, none of the dynamical models (with and without static friction) performed well on estimation of knee applied torque (see Tab. 4.2 and Fig. 4.8.C). Static friction is dominant due to the light weight of the lower limb segment in all frequencies and this makes the identification challenging at the knee joint.

Chapter 5

Human-exoskeleton Interaction Portrait

Human-robot physical interaction contains crucial information for optimizing user experience, enhancing robot performance, and objectively assessing user adaptation. This chapter introduces a new method to evaluate human-robot co-adaptation in lower limb exoskeletons by analyzing muscle activity and interaction torque as a two-dimensional random variable. We introduce the Interaction Portrait (**IP**), which visualizes this variable’s distribution in polar coordinates. We applied this metric to compare a recent torque controller (**HTC**) based on kinematic state feedback and a novel feedforward controller (**AMTC**) with online learning, proposed herein, against a time-based controller (**TBC**) during treadmill walking at varying speeds.

Compared to **TBC**, both **HTC** and **AMTC** significantly lower users’ normalized oxygen uptake, suggesting enhanced user-exoskeleton coordination. **IP** analysis reveals this improvement stems from two distinct co-adaptation strategies, unidentifiable by traditional muscle activity or interaction torque analyses alone. **HTC** encourages users to yield control to the exoskeleton, decreasing muscular effort but increasing interaction torque, as the exoskeleton compensates for user dynamics. Conversely, **AMTC** promotes user engagement through increased muscular effort and reduced interaction torques, aligning it more closely with rehabilitation and gait training applications. **IP** phase evolution provides insight into each user’s interaction strategy development, showcasing **IP** analysis’s potential in comparing and designing novel controllers to optimize human-robot interaction in wearable robots.

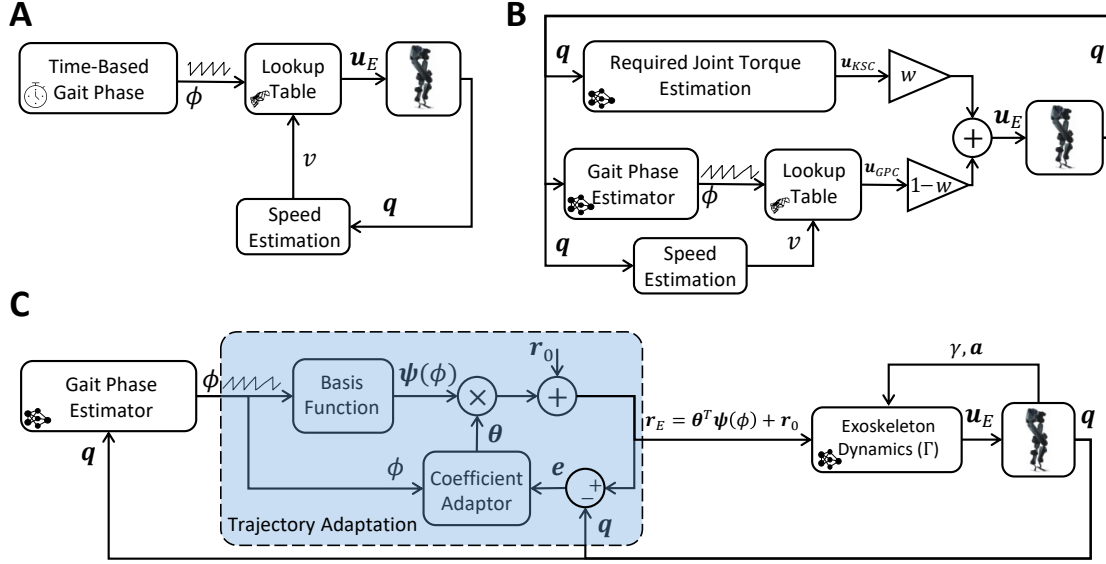


Figure 5.1: Block diagram of **TBC**, **HTC**, and **AMTC** controllers. **(A)** Block diagram of the Time-Based Controller (**TBC**). A time-based gait phase along with the estimated gait speed are fed into a lookup table to determine the applied torque to the exoskeleton joints according to joint torque data recorded from the exoskeleton during high-gain joint control with the user passively following the exoskeleton (with the minimum voluntary contribution to the gait). **(B)** The diagram of the Hybrid Torque Controller (**HTC**) consisted of a data-driven required joint torque estimator along with a look-up table-based torque controller similar to the **TBC**. In this case, however, the gait phase is determined according to the exoskeleton states rather than time. The torque from the two different pipelines is finally combined with the weight of w and $1-w$ to form the applied torque to the exoskeleton. **(C)** Block diagram of the Model-Based Torque Controller (**AMTC**). The gait phase is estimated according to the exoskeleton joint angles and then fed into a trajectory adaptation block which learns the joint trajectory of the participant in real time and uses that trajectory as the reference for the exoskeleton to be fed into the forward dynamics of the exoskeleton to determine the feedforward joint torques.

5.1 Methods

5.1.1 Feedforward Control Strategies

This section describes three controllers tested in our study.

Time-Based Torque Controller

Fig. 5.1A depicts the block diagram of the Time-Based Torque Controller (TBC). This controller utilizes lookup tables to determine the desired joint torques $\mathbf{u}_E$ by considering both the gait phase ($\phi(t)$) and the estimated gait speed (v). To construct the lookup table, measurements of exoskeleton joint torques were taken at different speeds while a participant walked with the exoskeleton governed by a high-gain PD controller. The participant was asked to exert the minimum voluntary effort during walking. The joint trajectories were controlled based on reference trajectories derived from the participant's walking without the exoskeleton. The input gait phase to the lookup table was obtained by dividing the stride length, calculated using the exoskeleton joint angles ($\mathbf{q}$), by the stride time updated at each heel strike. For this controller, the gait phase ($\phi(t)$) was generated based on the desired gait speed, following the formula $\phi(t) = \text{mod}(t, T)$, where T represents the average measured stride time when the participant walked without the exoskeleton at the desired gait speed. For more detailed information about the construction of the lookup table and the gait speed estimator, refer to [24].

Hybrid Torque Controller

Fig. 5.1B presents the block diagram of the Hybrid Torque Controller (HTC), which combines the torque outputs of two distinct controllers [23]: the Kinematic State Dependent Controller (KSC) and the Gait Phase Dependent Controller (GPC). The KSC incorporates an Artificial Neural Network (ANN) that calculates the required biological torque for the user based on the kinematic measurements of the exoskeleton [24]. On the other hand, the GPC adopts the same structure as the TBC mentioned earlier, however, instead of relying on a time-based gait phase, it utilizes a real-time estimation of the gait phase derived from the kinematic measurements [122]. The outputs of these two controllers are linearly combined in the HTC: $\mathbf{u}_E = w\mathbf{u}_{KSC} + (1 - w)\mathbf{u}_{GPC}$, where w represents the weight assigned to the KSC output.

Adaptive Model-based Torque Control

The Adaptive Model-based Torque Control (AMTC) depicted in Fig. 5.1C, leverages the estimated dynamics of the exoskeleton to generate joint torques for control. According to [123], the interaction between the Indego exoskeleton and the human in the sagittal plane can be described by the following dynamical model:

$$\mathbf{\Gamma}(\gamma, \dot{\gamma}, \ddot{\gamma}, \mathbf{a}, \mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{u}_E + \mathbf{u}_{int}, \quad (5.1)$$

where $\gamma \in \mathbb{R}$ and $\mathbf{a} \in \mathbb{R}^2$ denote the exoskeleton thigh segment angle with respect to the gravity vector and its acceleration in the sagittal plane, respectively, $\mathbf{q} = [q_{h,r}; q_{k,r}; q_{h,l}; q_{k,l}] \in \mathbb{R}^4$ represent the exoskeleton hip and knee joint angles, $\mathbf{u}_E \in \mathbb{R}^4$ denote the exoskeleton applied motor torques, and $\mathbf{u}_{int} \in \mathbb{R}^4$ represents the torques arising from the human-exoskeleton interaction. The [AMTC](#) controller employs a dynamic compensatory approach. In a dynamic compensator, the exoskeleton's applied torques are set equal to the exoskeleton's passive dynamics ($\mathbf{u}_E = \mathbf{\Gamma}(\gamma, \dot{\gamma}, \ddot{\gamma}, \mathbf{a}, \mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$) which ideally results in the transparency of the exoskeleton ($\mathbf{u}_{int} = 0$). However, in [AMTC](#), instead of using the current joint angles, the desired joint angles are used to compute the exoskeleton torques:

$$\mathbf{u}_E = \mathbf{\Gamma}(\gamma, \dot{\gamma}, \ddot{\gamma}, \mathbf{a}, \mathbf{r}_E, \dot{\mathbf{r}}_E, \ddot{\mathbf{r}}_E), \quad (5.2)$$

where $\mathbf{r}_E \in \mathbb{R}^4$ are the desired exoskeleton joint angles. This approach allows the exoskeleton to be transparent only when the user's joint motions align with the desired trajectories. Otherwise, the exoskeleton will assist or resist the user's motion depending on the consistency between the user's desired motion and the exoskeleton's desired trajectories. To ensure that the exoskeleton always assists the user and avoids resisting their motion, the reference trajectory of the exoskeleton needs to be synchronized temporally with the user's desired motion and matched spatially to their intended gait pattern. Temporal synchronization is achieved by defining the exoskeleton's reference trajectory as a function of the estimated gait phase computed from the exoskeleton's joint angles ($\mathbf{r}_E(t) = \mathbf{r}_E(\phi(\mathbf{q}))$). Spatial consistency is ensured by adapting the reference trajectory based on the minimization of the error between the exoskeleton's reference trajectory and its current joint angles ($\mathbf{e} = \mathbf{r}_E - \mathbf{q}$). At each joint, the reference trajectory is defined as $r_E = r_0(\phi) + \Delta(\phi)$, where r_0 represents the initial reference trajectory of the exoskeleton, and $\Delta(\phi) = \boldsymbol{\theta}^T \times \boldsymbol{\psi}(\phi)$ is the modification term. Here, $\boldsymbol{\psi}(\cdot)$ represents the Fourier series basis functions with up to m harmonics, and $\boldsymbol{\theta}$ represents the coefficients of the Fourier series that are adapted similar to [\[124\]](#). The adaptation rule is then derived to minimize $J = 0.5e^2$ using Gradient Descent (with a learning rate of ϵ):

$$\dot{\boldsymbol{\theta}} = -\epsilon \frac{\partial J}{\partial \boldsymbol{\theta}} = -\epsilon \frac{\partial J}{\partial e} \times \frac{\partial e}{\partial r_E} \times \frac{\partial r_E}{\partial \Delta} \times \frac{\partial \Delta}{\partial \boldsymbol{\theta}} = -\epsilon e \boldsymbol{\psi}(\phi). \quad (5.3)$$

5.1.2 Experimental Setup

The experimental setup comprised a split-belt instrumented treadmill (Bertec, US), with force plates under each belt, providing ground reaction forces ([GRF](#)) under each belt, a lower limb exoskeleton (Indego, Parker Hannifin, US) with actuated hip and knee joints,



Figure 5.2: Dorsal, lateral, and frontal view of a participant with the Indego exoskeleton with active hip and knee joints. The participant is standing on the Bertec treadmill with two speed-controlled belts equipped with individual loadcells underneath each of them for GRF monitoring. Muscle activation is measured from both right and left leg muscles using EMG sensors. Gait up IMUs are clipped to the outer side of the shoes right bellow ankle joints to measure the spatiotemporal parameters of gait. Oxygen uptake of the participant is measured and recorder at each breath through a mask connected to the gas analyzer device carried at the back of the participant.

fourteen wireless EMG sensors (Trigno, Delsys, USA), and a COSMED K5 wearable metabolic system (Albano Laziale, Roma, Italy) to measure oxygen uptake (VO_2). Additionally, four Physilog IMUs (Physilog 6s, Gait Up SA, CH) and a COSMED K5 wearable metabolic system (Albano Laziale, Roma, Italy) are employed to measure gait spatiotemporal parameters and oxygen uptake (VO_2), respectively. The exoskeleton, IMUs, load cells, and EMG sensors have sampling rates of 200 Hz, 128 Hz, 1000 Hz, and 2000 Hz, respectively. Following appropriate skin treatment, EMG sensors were placed on Gluteus Maximus, Biceps Femoris, Rectus Femoris, Vastus Medialis, Gastrocnemius Medialis, Soleus, and Tibialis Anterior muscles of each leg. Spatiotemporal gait parameters such as Minimum Toe Clearance (minTC), Maximum Heel Clearance (maxHC), Stance Time Percentage, and Stride Length are computed using the Physilog sensors, as validated in

previous studies [11, 114]. Before recording data for each subject, the COSMED K5 underwent a calibration process following a standardized procedure. Fig. 5.2 illustrates the exoskeleton and the placement of the sensors within the experimental setup.

5.1.3 Experimental Protocol

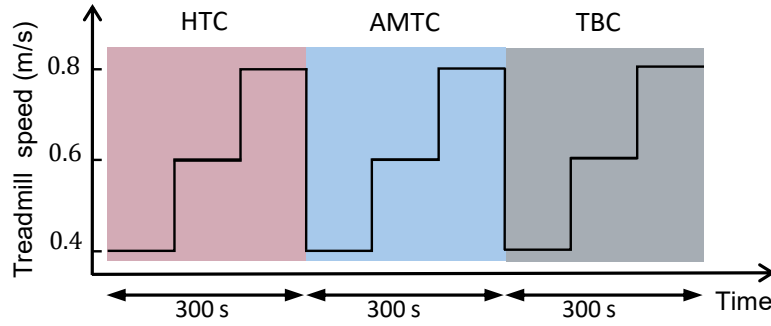


Figure 5.3: Treadmill speed changes while experimenting with the [HTC](#), [AMTC](#), and the [TBC](#) controller. The order of the controllers was specific to participant #1 and varied for other participants. Participants walked with each controller for 300 seconds divided by three 100-second walking periods during each the treadmill speed was set to ultra-slow (0.4 m/s), slow (0.6 m/s), and moderate (0.8 m/s) speeds.

The experiment consisted of three blocks, each involving participants walking on the treadmill with the exoskeleton controlled by one of three different controllers: [TBC](#), [HTC](#), or [AMTC](#). The order of the blocks was varied among participants to mitigate any potential order effects. Within each block, participants walked at three distinct speeds: ultra-slow (0.4 m/s), slow (0.6 m/s), and moderate (0.8 m/s). Each speed lasted for a duration of 100 seconds. For an illustration of the treadmill speed and the order of the controllers applied to the exoskeleton for participant #1, refer to [Fig. 5.3](#).

A total of nine able-bodied participants (5 males and 4 females, age: 23.4 ± 4.2 years, mass: 73.6 ± 20.2 kg, height: 176.7 ± 9.6 cm) participated in the study. All participants provided informed written consent prior to the experiments. The study protocol and procedures received ethical approval from the University of Waterloo Clinical Research Ethics Committee (ORE#41794). The study adhered to the principles outlined in the Declaration of Helsinki.

5.1.4 Data Analysis

Ground Reaction Force

Force plates are utilized to measure the ground reaction forces (GRF) in the vertical, lateral, and longitudinal directions. Heel strike events are detected using the vertical GRF, enabling the segmentation of collected data into individual strides. The recorded GRF during no exoskeleton walking is temporally normalized and averaged based on the gait phase as

$$\bar{\mathbf{f}}_v(\phi) = \text{mean}_{s \in S_v} \mathbf{f}_s(\phi),$$

where $v \in \{\text{ultra-slow, slow, moderate}\}$ is the treadmill speed index, $s \in \mathbb{N}$ is the stride index, S_v is the set of the strides during no exoskeleton walking with speed v , and $\mathbf{f}_s(\phi)$ is the temporally normalized GRF at stride s . To assess the similarity between the ground reaction force profiles with each controller and the natural walking without the exoskeleton, a normalized Pearson correlation is computed as

$$\mathbf{x}_{c,v,s} = \{\text{Corr}(\mathbf{f}_s(\phi), \bar{\mathbf{f}}_v(\phi)) | s \in S_{c,v}\},$$

where $S_{c,v}$ is the set of all strides during walking with exoskeleton at treadmill speed v with controller $c \in \{\text{TBC, HTC, AMTC}\}$.

Muscle Activation

The EMG data was bandpass filtered, with cutoff frequencies of 5 and 500 Hz. The signal was then full-wave rectified and its envelope was computed by applying a moving average with a window of 100 ms. Each EMG signal is normalized by its respective maximum voluntary contraction (Maximum Voluntary Contraction (MVC)), computed for each muscle as the maximum measured contraction during walking on the treadmill (maximum across with and without the exoskeleton walking). The average muscle effort [18,102] is computed for each muscle at each stride as

$$\mu_{m,s} = \frac{1}{T_s} \int_{T_s} e_m^2(t) dt,$$

where $e(t)$ is the filtered EMG signal, T_s is the duration of stride s computed by heel-strike events obtained from vertical GRF measurements, $m \in \{\text{Gluteus Maximus (GM), Biceps Femoris (BF), Rectus Femoris (RF), Vastus Medialis (VM), Medialis Gastrocnemius (MG),}$

Soleus (Sol), Tibialis Anterior (TA)}, is the muscle index. The muscle effort over all strides with controller c and speed v is, therefore, computed as

$$\mu_{c,v,m} = \sum_{s \in S_{c,v}} T_s \mu_{m,s},$$

where $S_{c,v}$ is the set of all strides taken with controller c and speed v . Finally, the total muscular effort ($\mu_{c,v}^{tot}$) was determined as the weighted average of the muscle efforts across all muscles. Physiological cross-sectional areas of muscles, obtained from [77], were employed as the weights for total muscular effort computation. This weighting scheme partly accounts for the differences in force contributions across muscles.

Interaction Torque

The human-exoskeleton interaction torque is estimated based on Eq. 5.1, given by

$$\mathbf{u}_{int} = \mathbf{\Gamma}(\gamma, \dot{\gamma}, \ddot{\gamma}, \mathbf{a}, \mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) - \mathbf{u}_E. \quad (5.4)$$

The mean absolute interaction torque is then calculated for each joint as:

$$\tau_{j,s} = \frac{1}{T_s} \int_{T_s} |u_{int,j}(t)| dt,$$

where $j \in \{\text{hip}_{\text{right}}, \text{knee}_{\text{right}}, \text{hip}_{\text{left}}, \text{knee}_{\text{left}}\}$ is the joint index. The overall absolute interaction torque with each controller is computed as

$$\tau_{c,v,j} = \sum_{s \in S_{c,v}} T_s \tau_{j,s}.$$

The total interaction torque ($\tau_{c,v}^{tot}$) is finally obtained for each controller as the average interaction torques across all joints.

VO2

VO2 is computed for each breath. To normalize the VO2 measurements across participants, the average VO2 during treadmill walking with no exoskeleton at each speed v is computed as:

$$\bar{\eta}_v = \text{mean}_{n \in N_v} \eta_n,$$

where n is the breath index and N_v is the set of all breaths during walking with no exoskeleton at treadmill speed v . The normalized VO2 during exoskeleton walking is then computed as

$$\hat{\eta}_{c,v,n} = \{\eta_n / \bar{\eta}_v | n \in N_{c,v}\},$$

where $N_{c,v}$ is the set of all breaths during walking with exoskeleton at treadmill speed v with controller c . The sum of the VO2 measurements is also obtained for all of the exhales for each controller as

$$\hat{\eta}_{c,v}^{tot} = \sum_{n \in N_{c,v}} \hat{\eta}_{c,v,n}.$$

Human-Exoskeleton Interaction Portrait (IP) Analysis

To examine the impact of each controller on the human-exoskeleton interaction dynamics, we analyzed the changes in total interaction torques ($\Delta\tau$) relative to variations in total muscular effort ($\Delta\mu$) when switching from controller c_1 to controller c_2 ($c_1 \rightarrow c_2$). For each treadmill speed (v), these changes are computed as:

$${}_{c_1}^{c_2} \Delta\tau_v^{tot} = \tau_{c_2,v}^{tot} - \tau_{c_1,v}^{tot}$$

$${}_{c_1}^{c_2} \Delta\mu_v^{tot} = \mu_{c_2,v}^{tot} - \mu_{c_1,v}^{tot}.$$

After normalizing $\Delta\tau$ and $\Delta\mu$ across participants and walking speeds, we investigate their variation with respect to each other. [Fig. 5.4](#) illustrates the possible outcomes:

- **Disagreement Increase ($\Delta\tau > 0$, $\Delta\mu > 0$)**

This condition is associated with an increase in both the total interaction torque and the total muscular effort, indicating that switching from controller c_1 to controller c_2 has led to an elevation of human muscular effort. Consequently, their contribution to motion has increased. This, however, has resulted in a higher total interaction torque with the exoskeleton, implying that the applied torques by the exoskeleton are not aligned with the user's desired motion. As a result, the user needs to exert additional effort to correct the motion while contending against the applied torques from the exoskeleton. Thus, the increased interaction indicates a lack of harmony between the user's intentions and the assistance delivered by the exoskeleton.

- **Disagreement Decrease ($\Delta\tau < 0$, $\Delta\mu < 0$)**

If controller c_2 demonstrates improved consistency compared to c_1 with the user's desired motion, the user will experience less resistance from the exoskeleton. This

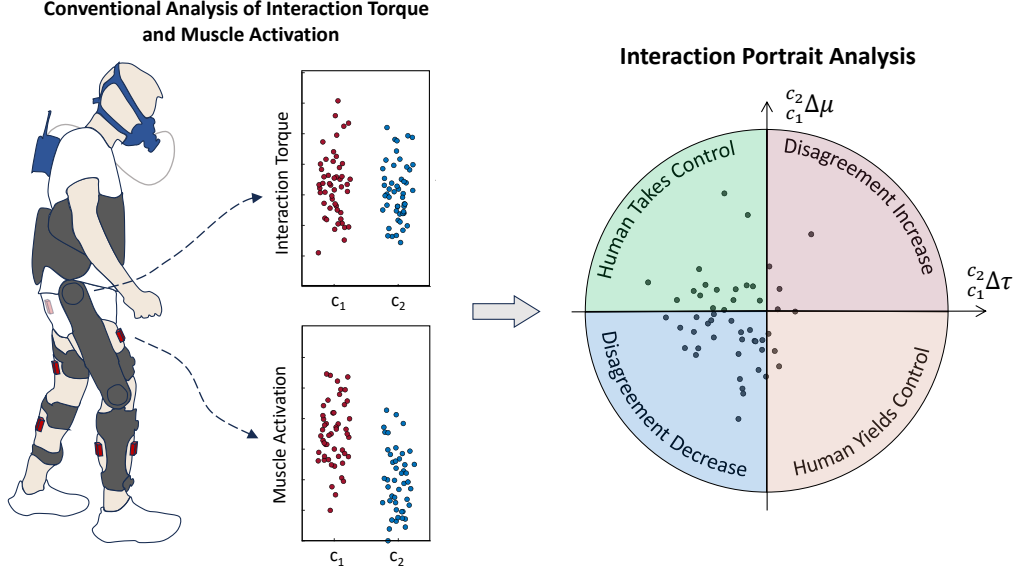


Figure 5.4: Regions of Interaction Portrait (IP). Each quadrant of the circle corresponds to different human-exoskeleton interaction modes determined by the variation of the normalized total muscle activation ($\frac{c_2}{c_1}\Delta\mu$) with respect to the normalized total interaction torque ($\frac{c_2}{c_1}\Delta\tau$) between controllers c_1 and c_2 , respectively. The first quadrant (red) indicates increased disagreement between the user and exoskeleton, resulting in an increase in both muscle effort and the total interaction torque. The second quadrant (green) determines the co-adaptation of the user toward participating in the motion as much as possible and leading the motion. The third quadrant (blue) denotes the decrease in total interaction torque and the total muscle effort, associated with the decrease in human-exoskeleton disagreement. Finally, the fourth quadrant (orange) denotes the condition at which the user yields control of the motion to the exoskeleton and minimally activates their muscles. In this case, muscle activation decreases while the total interaction increases since the exoskeleton has to carry the user's body (passive dynamics) in addition to the exoskeleton dynamics.

reduced discordance between the exoskeleton and the user's intended movements results in decreased total muscular effort and overall exertion by the user. Additionally, achieving a further reduction in disagreement between the human and exoskeleton can lead to one of the two next scenarios.

- **Human Yields Control to Robot ($\Delta\tau > 0$, $\Delta\mu < 0$)**

With the continued reduction in human-user interaction, a user may consider relinquishing motion control to the exoskeleton. This implies that the user will no longer actively contribute to the movement and will essentially deactivate their muscles, resulting in a decrease in overall muscular effort. Consequently, the exoskeleton must generate the necessary torque to facilitate the movement of both the exoskeleton and the passive dynamics of the human body. The increase in human-exoskeleton interaction torques, in this scenario, is not due to conflicts between the exoskeleton's motion and the user's desired motion but rather because the exoskeleton is effectively carrying the user's body.

- **Human Takes Control ($\Delta\tau < 0$, $\Delta\mu > 0$)**

In a contrasting scenario, the user may actively participate in the motion, resulting in an increased level of muscular effort. Consequently, the total interaction torque between the user and the exoskeleton may decrease. This reduction occurs because the human and exoskeleton motions are synchronized in time and consistent in space, creating a harmonious alignment between the two.

We conducted the aforementioned analysis at various speeds for the [TBC](#)→[BHTC](#), [TBC](#)→[AMTC](#), and [HTC](#)→[AMTC](#) cases. We also performed a stride-wise analysis for the [TBC](#)→[HTC](#) and [TBC](#)→[AMTC](#) scenarios, which involves computing changes of total interaction force and muscle effort at each stride during the [HTC](#) and [AMTC](#) controllers as

$$\begin{aligned} {}_{TBC}^c\Delta\mu_{v,s} &= \mu_{c,v,s} - \mu_{TBC,v}^{tot} \\ {}_{TBC}^c\Delta\tau_{v,s} &= \tau_{c,v,s} - \tau_{TBC,v}^{tot}, \end{aligned}$$

where $c \in \{\text{HTC}, \text{MBTC}\}$. These calculations allowed us to analyze the precise changes in interaction force and muscular effort for each stride during the [HTC](#) and [AMTC](#) controllers in relation to the [TBC](#) controller.

Interaction Portrait is a relative measure that compares human adaptation under different control strategies. If a baseline value is provided by a physical therapist or a reference controller, this metric can evaluate individual controllers. Additionally, Interaction Portrait offers clinicians an abstract metric that quantifies human-exoskeleton interaction during a gait cycle, allowing objective tuning of the exoskeleton assistance strategy.

Statistical Analysis

To identify statistical differences, we initially employed a Friedman test with a significance level of 0.05 to test group-level differences. Following the Friedman test, we conducted

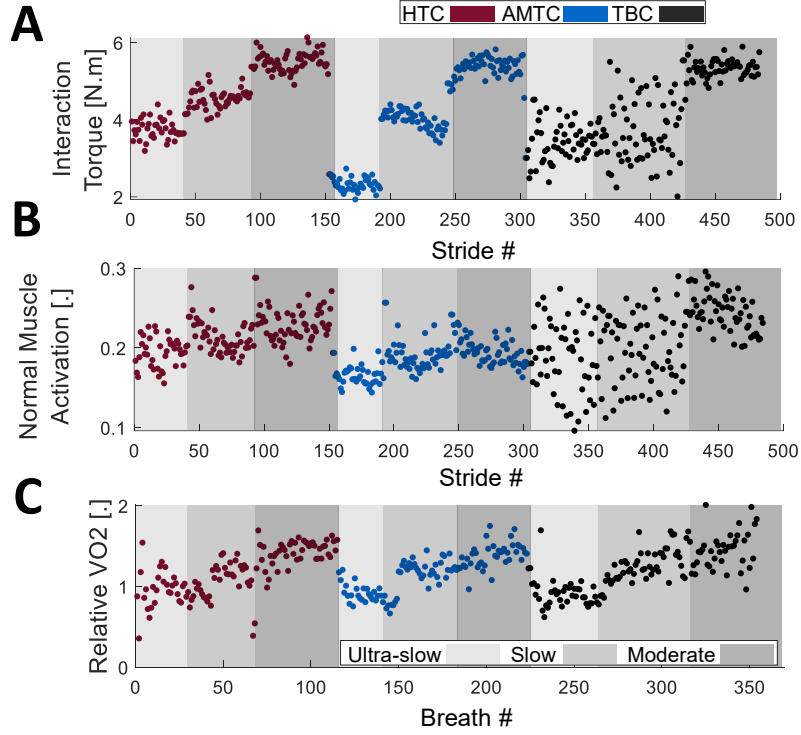


Figure 5.5: A portion of a typical participant’s experimental data; for ease of visualization and interpretation, the interaction torque at the right hip and activation of one of the muscles are illustrated along with the relative oxygen uptake. **(A)** The mean absolute interaction torque at the right hip at each stride with each controller and speed for Participant #1. **(B)** Normal muscle activation for the Gastrocnemius Medialis at the right leg. **(C)** Relative oxygen uptake for each breath for each controller and speed. The oxygen uptake has increased with the increase in treadmill speed.

pairwise comparisons, between the blocks, using the Wilcoxon signed-rank test. To account for multiple comparisons between the three blocks, we applied the Bonferroni correction.

5.2 Results

5.2.1 Initial Processed Data for a Representative Participant

Fig. 5.5 showcases some of the signals obtained from a typical participant (Participant #1) during robot-assisted treadmill walking with different controllers. Fig. 5.5A shows the mean absolute interaction torque at the right hip joint (as one of the four joints we computed interaction torque about) for each stride. The interaction torque increases with an increase in treadmill speed across all blocks. During ultra-slow and slow walking, AMTC interaction torques are smaller than those of HTC and TBC. Fig. 5.5B shows Gastrocnemius Medialis (GM) activation ($\mu_{c,v,m}$), selected for visualization here as an example from seven muscles recorded on each leg, for each stride. Similar to the interaction torques, muscular effort increases at higher treadmill speeds, mostly during the HTC and TBC blocks. In the AMTC block, however, GM’s muscular effort does not change from slow to moderate speeds. Moreover, the muscular effort is smaller during the AMTC block compared to the two other blocks. The relative oxygen uptake ($\eta_{c,v}$) during the experiment for breath cycles is presented in Fig. 5.5C. As anticipated, the oxygen uptake increases with an increase in treadmill speed in the HTC, AMTC, and TBC blocks.

5.2.2 Overall Performance Analysis

Fig. 5.6A shows the sum of the oxygen uptake for participants for each of the TBC, HTC, and AMTC blocks during ultra-slow, slow, and moderate-speed walking. TBC and AMTC have the highest and lowest metabolic rate at all walking speeds, respectively. The AMTC-resultant metabolic rate is significantly less than other controllers, at ultra-slow and slow walking, where AMTC resulted in $22.9\% \pm 17.1$ (Friedman: $p < 0.03$, Wilcoxon signed rank: $p_{TBC,AMTC} < 0.01$) and $28.7\% \pm 12.7$ (Friedman: $p < 0.005$, Wilcoxon signed rank: $p_{TBC,AMTC} < 0.003$) decrease in the total oxygen uptake, respectively. The total mean absolute interaction torque is similarly illustrated for the participants in Fig. 5.6B. AMTC has the lowest interaction torque compared to TBC and HTC, indicating the least disagreement between the exoskeleton assistance and the user desired motion. With respect to the TBC, AMTC shows $17.1 \pm 12.5\%$, $12 \pm 15\%$, and $9.2 \pm 7.7\%$ of reduction in human-exoskeleton total interaction in ultra-slow, slow, and moderate-speed walking, respectively. The difference is statistically significant at the ultra-slow walking (Friedman: $p < 0.04$, Wilcoxon signed rank: $p_{TBC,AMTC} < 0.01$). Compared to HTC, AMTC shows $19.8 \pm 21.1\%$, $17.9 \pm 10.1\%$, and $18.1 \pm 9.9\%$ reduction in human-exoskeleton total interaction. These differences are statistically significant in the case of slow (Fridman: $p < 0.03$, Wilcoxon signed

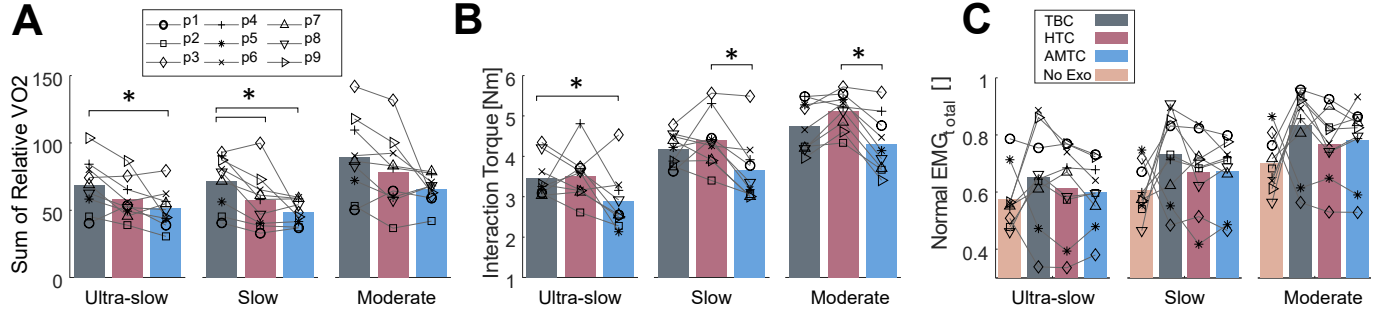


Figure 5.6: The average performance metrics for each treadmill speed and controller across participants. **(A)** The sum of the relative oxygen uptake across all the strides for each speed in each controller block graphed for each participant. The bars show the average of the sum of the oxygen uptake across all participants. Similarly, the average total absolute value of the human-exoskeleton interaction and total normalized muscle effort are graphed in **(B)** and **(C)**, respectively.

rank: $p_{HTC,AMTC} < 0.004$) and moderate-speed (Fridman: $p < 0.0008$, Wilcoxon signed rank: $p_{HTC,AMTC} < 0.004$) walking. Fig. 5.6C shows the total muscle effort for participants' right legs during ultra-slow, slow, and moderate-speed walking across the three different controllers. Natural walking without the exoskeleton has the lowest total muscle effort compared to other cases in which the exoskeleton is involved. This is expected as wearing the exoskeleton adds about 17 kg of extra weight to the body resulting in higher muscle effort. Among the three controllers, TBC has the highest total muscular effort at all speeds. AMTC and HTC's total muscular effort are close in all cases while AMTC is slightly lower and higher in ultra-slow and moderate speeds, respectively. None of the identified differences are statistically significant.

5.2.3 Interaction Portrait Analysis

Fig. 5.7 compares the examined controllers one by one in ultra-slow, slow, and moderate-speed walking by illustrating the average change in the max-normalized total muscular effort with respect to the change in the max-normalized total interaction torque (the average IP is plotted by a single vector for each participant). To compare the IP results of participants more easily, Fig. 5.7A shows the average IP for HTC compared to TBC, denoted as $[\frac{HTC}{TBC} \Delta \tau_v^{tot}, \frac{HTC}{TBC} \Delta \mu_v^{tot}]$. In ultra-slow and slow walking, participants adapt differently to HTC compared to TBC, as the average IP, indicated by vectors, are spread in

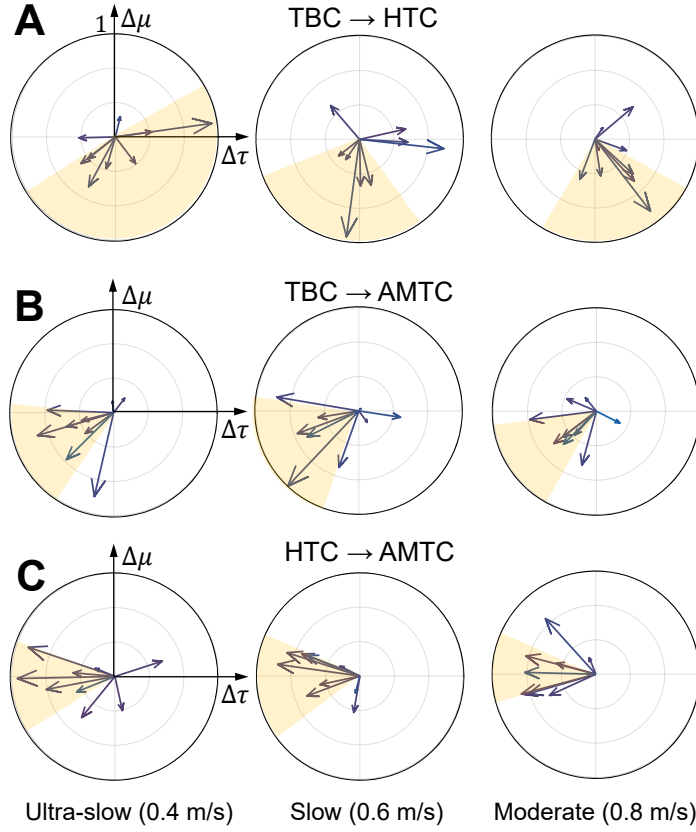


Figure 5.7: Comparing the Average Interaction Portrait for each Pair of Controllers. The average Interaction Portrait (IP) depicted according to the average total muscle effort and the average total human-exoskeleton interaction for each participant computed at each of the ultra-slow, slow, and moderate-speed walking for the **TBC**→**HTC**, **TBC**→**AMTC**, and **HTC**→**AMTC** illustrated in (A), (B), and (C), respectively. The yellow areas denote the area between the 25 and 75 percentiles.

all quadrants. In moderate speed, however, the majority of average IP vectors fall within the fourth quadrant, indicating that most participants yield control to the **HTC**-controlled exoskeleton. This observation aligns with participants exhibiting the lowest total muscular effort when walking with an **HTC**-controlled exoskeleton, as shown in Fig. 5.6C. Similarly, Fig. 5.7B presents the average IP vectors of **AMTC** compared to **TBC**, denoted by $[\overset{AMTC}{TBC} \Delta \tau_v^{tot}, \overset{AMTC}{TBC} \Delta \mu_v^{tot}]$. Unlike **HTC**, **AMTC** effectively decreases user-exoskeleton disagreement at all tested speeds, as indicated by the majority of average IP vectors con-

centrated in the third quadrant. To further examine, Fig. 5.7C compares the HTC and AMTC controllers, denoted as $[\Delta\tau_v^{tot}, \Delta\mu_v^{tot}]_{HTC}^{AMTC}$. It shows that at all walking speeds, participants lean more toward contributing to the motion rather than yielding control to the exoskeleton, as most of the average IP vectors fall around the border of the second and third quadrants.

5.2.4 Individual Adaptation Strategy

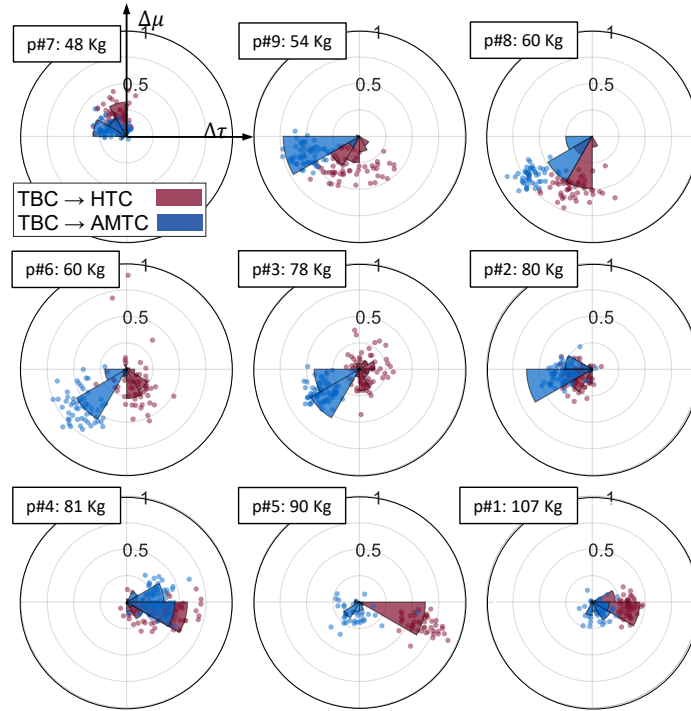


Figure 5.8: Comparison of the Interaction Portrait distribution between TBC→HTC and TBC→MTBC. Interaction portrait distribution for HTC and AMTC blocks with respect to the average total muscle effort and total interaction torque across all strides during the TBC block graphed for each participant plotted for moderate speed walking. The radius of data points is normalized with respect to the maximum radius computed across all participants' strides. Participants are arranged increasingly according to their body mass. The polar histograms show the concentration intensity of the depicted points. Each bin of the histogram covers $\pi/6$ rad.

We analyzed the dependency of user adaptation strategy formed in interaction with

each of the **HTC** and **AMTC** cases with respect to the **TBC**. To this end, we computed the average total muscular effort and interaction torque in **TBC**. We then computed the total muscular effort and interaction torque for each stride in the **HTC** and **AMTC** cases. For each stride, the difference in total muscle effort and interaction torque is then computed with respect to the **TBC**. Fig. 5.8 shows the stride-wise **IP** distribution of the **TBC**→**HTC** ($[\frac{HTC}{TBC} \Delta \tau_{v,s}, \frac{HTC}{TBC} \Delta \mu_{v,s}]$ in red), and **TBC**→**AMTC** ($[\frac{AMTC}{TBC} \Delta \tau_{v,s}, \frac{AMTC}{TBC} \Delta \mu_{v,s}]$ in blue) for each participant separately during moderate speed walking. The graphs are ordered from left to right and top to bottom, corresponding to a monotonic increase in participants' body mass. According to the graph, except for participant #7, our lighter participants leaned towards contributing more to the gait and leading the motion, with either **HTC** or **AMTC**, as their **IP** is consistently distributed in the third quadrant. Conversely, heavier participants in our experiment showed a tendency to relinquish control and passively follow the exoskeleton. This tendency is more pronounced in the case of the two heaviest participants who consistently adopted such a strategy in the case of **HTC**, with their **IP** distribution falling in the fourth quadrant, while their **IP** distribution for the **AMTC** is spread over a wider area. The strength of the adopted co-adaptation strategy is proportional to the radius of the **IP** distribution. Accordingly, the higher radius of **TBC**→**AMTC** **IP** distribution compared to **TBC**→**HTC** in the case of participants #9, 8, 6, and 3 reveals that **AMTC**-controlled exoskeleton led users to adopt a more consistent strategy compared to the **HTC** case. Participants #5 and 1, as exceptions, adopted a more consistent strategy during **HTC**. Fig. 5.8 also reveals that Participant #1 did not adopt a strong strategy in either the **HTC** or **AMTC** cases.

5.3 Discussion

5.3.1 Human Adaptation

An interesting observation in Fig. 5.5 is the variation in metrics associated with the **TBC** controller. For instance, Participant #1 experienced varying interaction torques at ultra-slow and slow walking speeds, as shown in Fig. 5.5A. Conversely, at moderate-speed walking, the variation in the interaction torque decreases, demonstrating a more consistent performance by the participant. A similar observation is evident in the case of **GM** muscle activation (Fig. 5.5B). For further investigation, Fig. 5.9 illustrates the average profile of **GM** activation and hip interaction torque, temporally normalized with respect to the gait phase at ultra-slow, slow, and moderate-speed walking. Both metrics exhibit a large standard deviation (shaded area) during ultra-slow and slow walking, while the standard

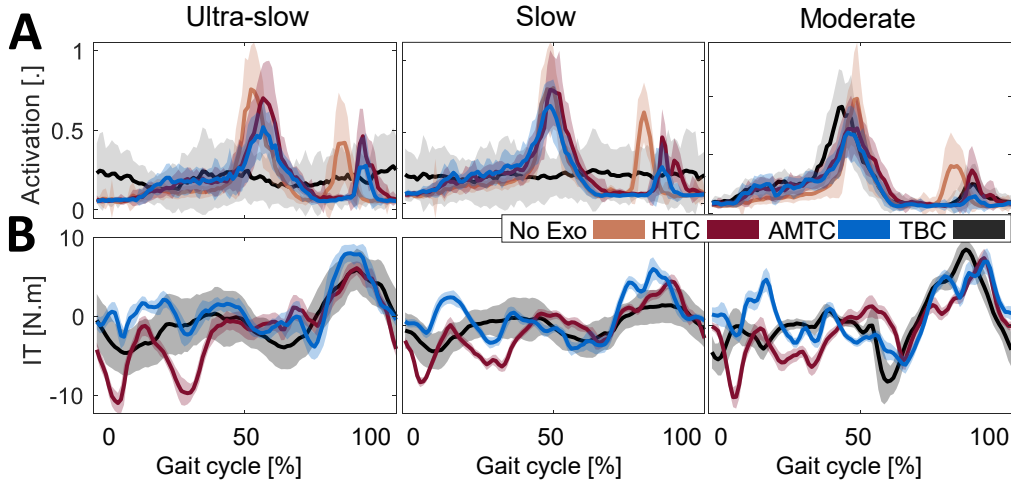


Figure 5.9: Muscle activation and interaction torque profile with respect to the gait phase. **(A)** The average normalized muscle activation pattern for the **TBC**, **HTC**, and **MBTC** blocks for the right Gastrocnemius Medialis during ultra-slow, slow, and moderate-speed walking. The shaded area represents the standard deviation of the muscle activation about their mean value. Similarly, the average human-exoskeleton interaction torque at the right hip is plotted in **(B)**.

deviation significantly drops during moderate-speed walking. This indicates an inconsistency in the participant's performance in both spatial and temporal aspects.

The inherent difference between the **TBC** and the other two controllers can explain this observation. During the **TBC** block, the feedforward torque is generated regardless of the user's performance, and the exoskeleton has no capacity for adapting to the user. Therefore, it is entirely up to the user to adapt to the torque delivered by the exoskeleton. In ultra-slow and slow walking, the participant was unable to adjust their gait timing to the exoskeleton, resulting in inconsistent interaction with the exoskeleton. At the higher speed, however, the user was able to synchronize their gait with the exoskeleton assistance and, therefore, adopted a solid interaction strategy, which emerges as a lower variation in all the above metrics. This has not been the case for all participants, as six of them were not successful in effectively synchronizing their walking to the **TBC**-controlled exoskeleton assistance at any speed. These results highlight the importance of human-robot co-adaptation, which is not achievable with a time-based controller.

5.3.2 Importance of IP Analysis

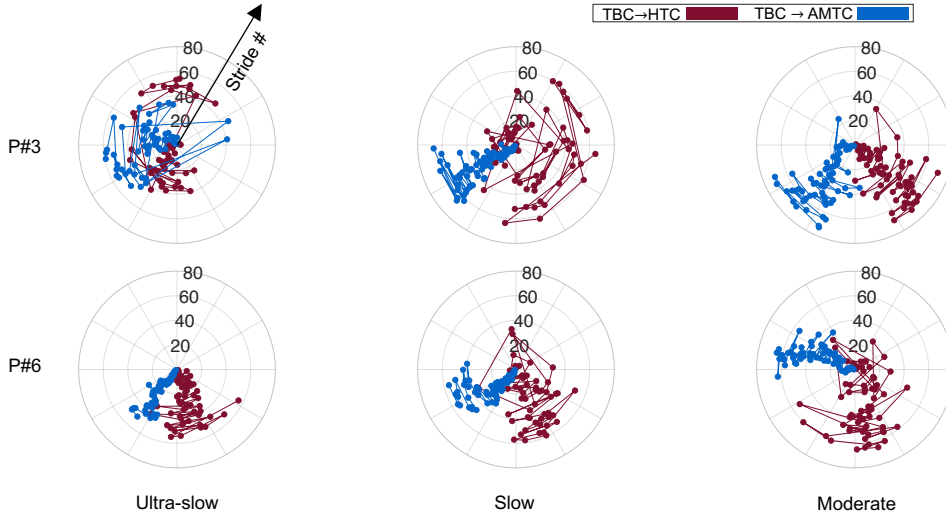


Figure 5.10: Evolution of IP phase at each stride at different walking speeds for two sample participants. The top and bottom rows depict IP phase evolution at ultra-slow, slow, and moderate speed walking for each of the TBC → HTC and TBC → AMTC cases for participants #3 and #6, respectively.

In Fig. 5.6A, the lower total muscular effort during walking with the HTC and AMTC compared to TBC is consistent with their lower metabolic rate with respect to the TBC, indicating that both controllers reduce the walking effort more than the TBC-controlled exoskeleton. However, a similar trend has not been observed in the total interaction torque, where HTC resulted in higher interaction torque compared to the TBC. This indicates that even though HTC and AMTC both reduced users' metabolic rate and muscular effort, they encouraged users to adopt two different interaction strategies. IP analysis further investigates the effect of each controller on the performance of each participant by analyzing the difference in total muscular effort with respect to the difference in total human-exoskeleton interaction torque. Fig. 5.7 reveals that the decrease in metabolic rate occurred based on two different human adaptation strategies. In the HTC controller, users relinquished control to the exoskeleton, passively following the exoskeleton's motion. In contrast, AMTC encouraged users to lead the motion more actively. Our IP analysis suggests that the HTC controller is particularly well-suited for applications requiring power augmentation, such as in industrial settings for workers or healthcare environments for nurses. In these contexts,

the primary goal is to minimize human exertion, thereby enhancing operational capabilities and safety. Conversely, the [AMTC](#) controller shows greater promise in rehabilitation contexts for individuals with residual motor functions, such as those with incomplete spinal cord injuries or post-stroke conditions. Here, the imperative is to actively involve the user in task execution, thereby amplifying their motor functions and accelerating recovery processes.

[Fig. 5.7](#) also demonstrates that different participants adopted a more consistent strategy with [AMTC](#) compared to the [HTC](#), as the average [IP](#) vectors across participants exhibit lower variation with [AMTC](#) compared to the [HTC](#) controller.

[IP](#) distribution itself can also shed light on the strength of the adopted strategy in each participant depending on the radius of the vectors forming the [IP](#). This is more evident in [Fig. 5.8](#) where each point of [IP](#) represents the difference in muscle effort and interaction torque obtained for each stride. As an example, the [IP](#) analysis in [Fig. 5.8](#) reveals that Participant #3 (2nd row, 2nd column) and Participant #6 (2nd row, first column) adopted the same interaction strategy with the [AMTC](#) controller compared to the [TBC](#). This is, nevertheless, more significant for Participant #6 due to the larger radius of the distributed points compared to those of Participant #3.

Using the [IP](#) analysis, it is also possible to track the evolution of the adopted strategy across the stride at each walking speed. [Fig. 5.10](#), as an example, shows the evolution of the [IP](#) phase for each of the [TBC](#)→[HTC](#) and [TBC](#)→[AMTC](#) comparisons for participants #3 and #6, respectively. Implied by the large variation in the [IP](#) phase, Participant #3 did not converge to a consistent interaction strategy with neither the [HTC](#) nor [AMTC](#) controllers during ultra-slow walking. This lack of convergence to a consistent interaction with the exoskeleton agrees with our difficulty in maintaining smoothness and continuity of ultra-slow movements, possibly explained by limitations of dynamic primitives that often lead to segmented movements (Park, et al., 2017). In slow walking, however, the user adopted a more consistent strategy using [AMTC](#), evidenced by low variations in the [IP](#) phase. In the case of the [HTC](#) controller, the participant’s strategy remains inconsistent. Only in the case of moderate-speed walking was Participant #3 able to converge to consistent interaction strategies both with the [AMTC](#) and the [HTC](#) controllers. Our [IP](#) analysis in this case shows that [AMTC](#) decreased the human-exoskeleton interaction, but the user did not completely obtain the motion control or yield the motion to the exoskeleton, as the [IP](#) phase is still in the third quadrant. In the case of the [HTC](#) controller, the user has relied more on the exoskeleton assistance since the [IP](#) phase is primarily concentrated in the 4th quadrant. Participant #6, in contrast to Participant #3, converged to a consistent interaction with the exoskeleton at all three walking speeds. The [HTC](#) controller, regardless of the walking speed, has guided the participant to rely more on the exoskeleton as the [IP](#)

phase is mostly concentrated on the border of the 3rd and 4th quadrants. In the case of the [AMTC](#) controller, however, we observe that as the gait speed increases, the user strategy develops more toward leading the gait and contributing to motion control, evidenced by an 83-degree shift in the average [IP](#) phase in moderate-speed walking compared to ultra-slow walking.

These results showcased the ability of [IP](#) analysis to provide an objective comparison of different exoskeleton controllers, the adopted interaction strategy by the user, as well as evaluating user-exoskeleton co-adaptation. Besides offline analysis, [IP](#) provides designers with a quantitative metric that can be tuned in a human-in-the-loop optimization setting to tailor the exoskeleton controller to the unique requirements of each application or participant.

5.4 Conclusion

We proposed a new metric for the analysis of human-exoskeleton interaction (Interaction Portrait) and employed it in investigating the effect of three feedforward controllers in enhancing human-exoskeleton interaction during assisted treadmill walking at different speeds. Through interaction portrait analysis, we found that the [HTC](#) controller demonstrated a more suitable performance for power augmentation along with reducing muscle activation and metabolic cost. On the other hand, the [AMTC](#) controller, also proposed in this study, proved to be more suitable for rehabilitation applications, as it promoted user reliance on their own muscular capacity by making the exoskeleton transparent.

Furthermore, we observed that the human adaptation pattern facing each of the [HTC](#) and [AMTC](#) controllers was influenced by the participants' weight. Individuals with lower weight tended to take control with the [AMTC](#) controller, while heavier participants were more inclined to relinquish control when interacting with the [HTC](#)-controlled exoskeleton. [IP](#) analysis has been only performed to evaluate the able-bodied individuals' interaction with exoskeletons. As the next step of this research, we plan to analyze the interaction portrait of motor-impaired individuals with exoskeletons equipped with different assist as needed controllers to provide a meaningful and objective comparison of these controllers. In this work, user physical interaction and muscular effort under the baseline controller were averaged across gait cycles. For each step of the tested controllers, the distance from these means was calculated to obtain the [IP](#) distributions. If the baseline controller measurements are skewed, a Bayesian approach or Mahalanobis distance could offer a more accurate comparison. Therefore, developing a probabilistic Interaction Portrait analysis is a future direction of this work.

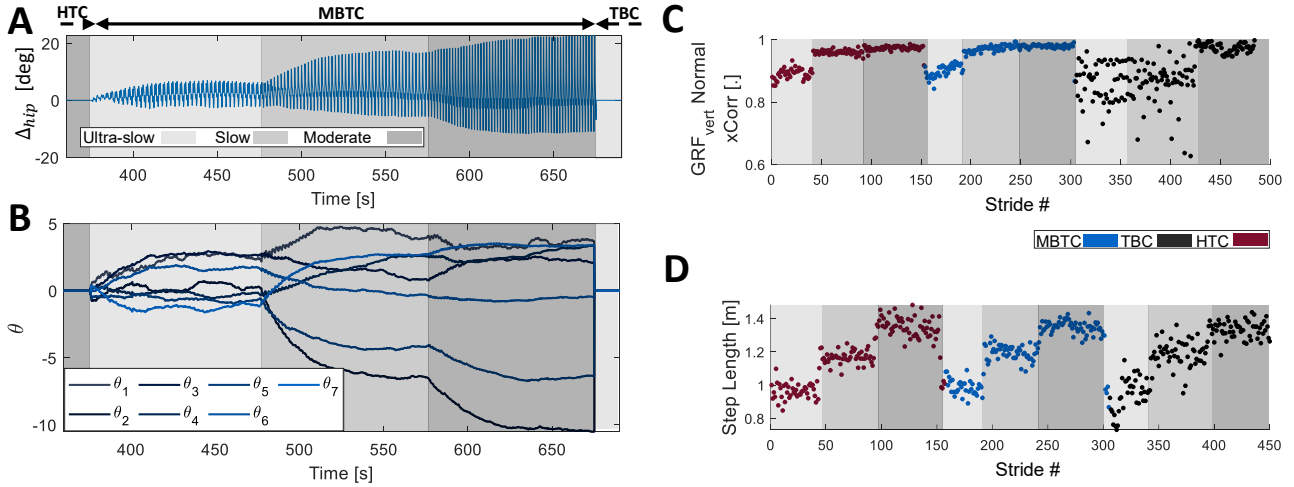


Figure 5.11: (A) Evolution of the modification term for Participant #1's right hip trajectory (Δ_{hip}). Δ_{hip} is zero before and after the AMTC block. During the AMTC block, the modification term of the trajectory adapts to make the reference trajectory closer to the user joint angle. At each of the ultra-slow, slow, and moderate walking speeds, the modification pattern in the steady state converges to a different amplitude and shape, indicating that the user joint angle, and as a result, the exoskeleton reference trajectory has evolved to a different pattern at each speed. (B) Modification trajectory coefficients evolve during the AMTC block. Each coefficient has converged to a steady state value at the end of each treadmill speed condition. After the change in treadmill speed, coefficients converge to new optimum levels. These levels, as mentioned for the modification term of the hip trajectory, differ for each speed. (C) Pearson correlation between the GRF of each stride with the average GRF profile recorded during natural walking without the exoskeleton. (D) Stride length computed using the Physiolog 6s IMU sensors.

5.5 Supplementary Material: Complementary Example

Fig. 5.11A illustrates the modifications made to the hip reference trajectory (Δr_{hip}) during the AMTC block. These modifications occur after the HTC block and before the TBC block, as depicted in (Fig. 5.3), across ultra-slow, slow, and moderate walking speeds. Similarly, Fig. 5.11B showcases the adaptation of the Fourier coefficients (θ) and their convergence pattern during the AMTC block at ultra-slow walking. The Fourier coefficients begin to adapt as soon as that block starts. It takes approximately 20 seconds for them to converge, and they subsequently exhibit minor oscillations around their converged values until the treadmill speed is switched to the slow speed. This change in treadmill speed

induces new walking conditions, resulting in distinct gait patterns. Consequently, the Fourier coefficients converge toward a new set of steady-state values. A similar pattern emerges when the treadmill is switched to the moderate speed. Pearson correlation between the vertical Ground Reaction Forces during each of the [HTC](#), [AMTC](#), and [TBC](#) blocks and natural walking with no exoskeleton is plotted for each stride in [Fig. 5.11C](#). According to the graph, the [GRF](#) patterns resemble the [GRF](#) in natural walking at slow and moderate walking speeds. In ultra-slow speed, however, the correlation slightly decreases in all three blocks. Finally, [Fig. 5.11D](#) shows the computed stride length. As expected, in all three blocks, the stride length increases with the increase in treadmill speed.

5.6 Supplementary Material: Comparison with Natural Walking

To identify which controller led to a gait closer to natural walking, we analyzed the spatiotemporal parameters of gait (obtained using GaitUp Sensors) in [TBC](#), [HTC](#), and [AMTC](#) and compared them to those of each participant’s natural walking with no exoskeleton. Moreover, we analyzed the correlation of recorded ground reaction torques in the case of each controller with natural walking.

5.6.1 Gait Spatiotemporal Parameters

[Fig. 5.12A](#) shows the maximum heel clearance in natural walking condition (with no exoskeleton) and during exoskeleton walking at each of the [TBC](#), [HTC](#), and [AMTC](#) blocks at ultra-slow, slow, and moderate speeds. Natural walking has the greatest heel clearance, which is expected as the addition of the exoskeleton weight makes it harder for the participant to lift their foot to their convenient level. Among the three controllers, [AMTC](#) has a heel clearance closer to that of natural walking, indicating that maintaining the desired heel clearance is easier for the participant in the case of this controller. Similarly, [Fig. 5.12B](#) compares the minimum toe clearance, showing that at all walking speeds, natural walking with no exoskeleton has the lowest minimum toe clearance. The [HTC](#) controller demonstrates lower toe clearance than the [TBC](#) and [AMTC](#) at all speeds. However, these differences are not statistically significant unless during moderate walking, where the [HTC](#) has led to a $21.3\% \pm 18.2$ and $12.2\% \pm 9.3$ decrease in minimum toe clearance compared to the [AMTC](#) and [TBC](#), respectively (Friedman: $p < 0.001$, Wilcoxon signed rank: $p_{HTC,AMTC} < 0.007$, $p_{HTC,TBC} < 0.003$).

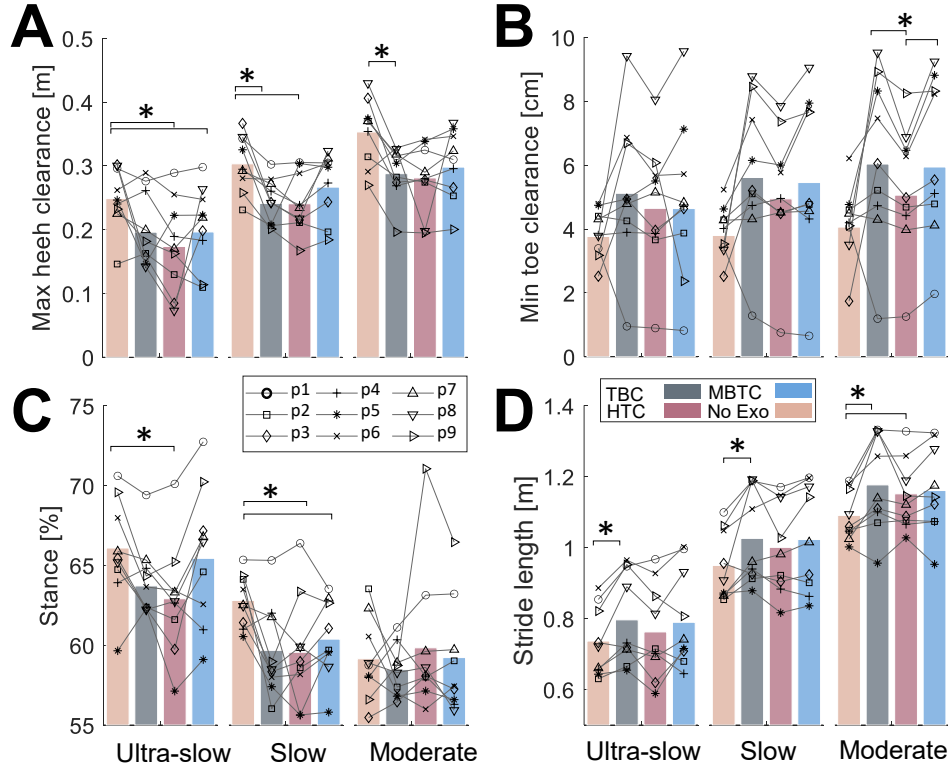


Figure 5.12: The average maximum heel clearance (A), minimum toe clearance (B), stance percentage (C), and stride length (D), computed for each of the ultra-slow, slow, and moderate speeds during natural walking with no exoskeleton, TBC, HTC, and the AMTC blocks for each participant. Bars show the average of each metric across participants.

Regarding the stance percentage, as depicted in Fig. 5.12C, AMTC exhibits the closest behavior to natural walking at all speeds. In all cases, TBC has a smaller stance percentage compared to natural walking. During ultra-slow and slow-speed walking, HTC has the smallest stance percentage. In moderate-speed walking, however, HTC has the highest stance percentage. Finally, Fig. 5.12D illustrates the stride length for each of the controllers at the three experimented walking speeds. The stride length generally increases with the increase in treadmill speed. At each individual speed, however, natural walking appears to have the smallest stride length on average, mostly compared to the TBC, which has the highest stride length (Friedman: $p < 0.05$, Wilcoxon signed rank: $p < 0.01$ for all speeds).

5.6.2 Ground Reaction Force

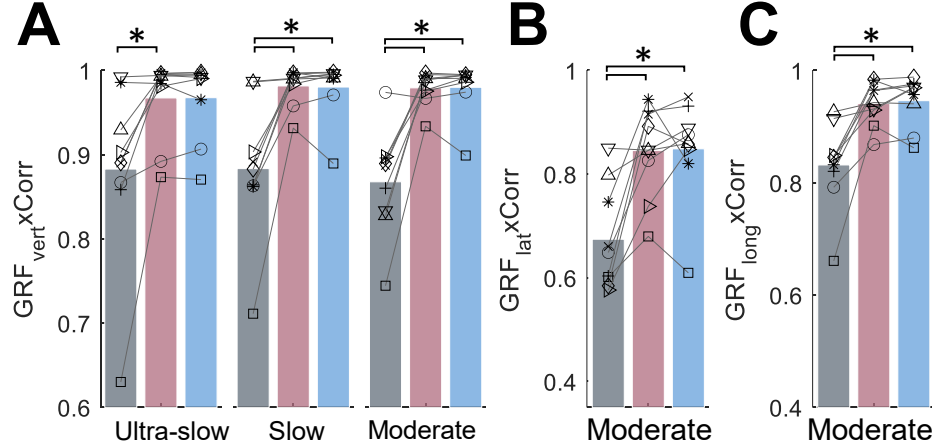


Figure 5.13: (A) The average Pearson correlation computed between the average vertical GRF in natural walking without the exoskeleton and the vertical GRF during walking with each of the proposed controllers at different speeds. Depicted bars show the average of each metric across participants. (B) and (C) shows the similar graph for the lateral and longitudinal GRF plotted only during the moderate speed.

Fig. 5.13A shows the Pearson correlation of the vertical ground reaction force between walking with each of the controllers and natural walking without the exoskeleton. At all speeds, TBC exhibits the most different vertical GRF compared to the other controllers (Friedman: $p_{\text{Ultra-slow}} < 0.02$, $p_{\text{Slow}} < 0.001$, and $p_{\text{Moderate}} < 0.016$; Wilcoxon signed rank: $p < 0.01$ for all speeds). In contrast to the TBC, HTC and AMTC led to more natural vertical GRF profiles with Pearson correlations greater than 96% at all speeds. The same observation stands for the GRFs in lateral (Fig. 5.13B) and longitudinal (Fig. 5.13C) directions, where TBC shows the least natural GRF profile while HTC and AMTC demonstrate closer to natural walking GRF with Pearson correlations greater than 82.2% and 91.5% in lateral and longitudinal directions, respectively (Friedman: $p < 0.003$; Wilcoxon signed rank: $p < 0.004$ for all cases).

Chapter 6

Online Reference Trajectory Adaptation: A Personalized Control Strategy for Lower Limb Exoskeletons

This chapter presents a novel method for reference trajectory adaptation in lower limb rehabilitation exoskeletons during walking. Our adaptation rule is extracted from a cost function that penalizes both interaction force and trajectory modification. By adding trajectory modification term into the cost function, we restrict the boundaries of the reference trajectory adaptation according to the patient's motor capacity. The performance of the proposed adaptation method is studied analytically in terms of convergence and optimality. We also developed a realistic dynamic walking simulator and utilized it to analyze our method. The proposed trajectory adaptation technique guarantees convergence to a stable, reliable, and rhythmic reference trajectory with no prior knowledge about the human intended motion. Our simulations demonstrate the convergence of exoskeleton trajectories to those of simulated healthy subjects while the exoskeleton trajectories adapt less to the trajectories of patients with reduced motor capacity (less reliable trajectories). Furthermore, the gait stability and spatiotemporal parameters such as step time symmetry and minimum toe clearance were enhanced by the adaptation in all subjects. Our mathematical analysis and simulation results show the applicability and effectiveness of the proposed method and its potential to be used in lower limb rehabilitation exoskeletons.

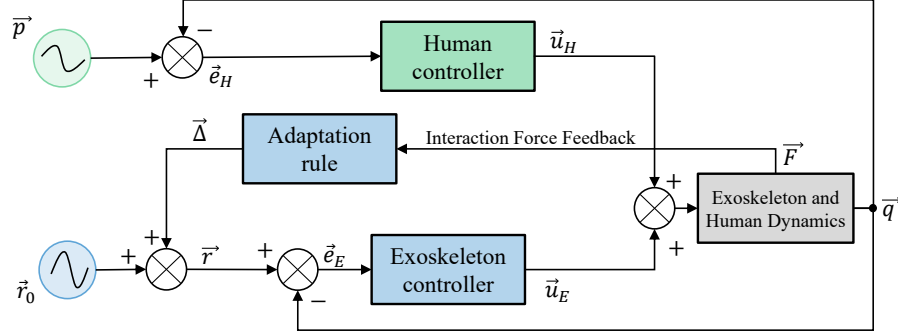


Figure 6.1: Human and exoskeleton dynamical interaction block diagram. The exoskeleton reference trajectory ($\mathbf{r}(t)$) is adapted based on the feedback from interaction force ($\mathbf{F}$). Human and exoskeleton controllers try to minimize their tracking error.

6.1 Problem Statement

Human-exoskeleton interaction dynamics (Fig. 6.1) is

$$\mathbf{\Gamma}_H(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{u}_H + \mathbf{F} \quad , \quad \mathbf{\Gamma}_H(.) : \mathbb{R}^{n \times n \times n} \rightarrow \mathbb{R}^n \quad (6.1)$$

$$\mathbf{\Gamma}_E(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{u}_E - \mathbf{F} \quad , \quad \mathbf{\Gamma}_E(.) : \mathbb{R}^{n \times n \times n} \rightarrow \mathbb{R}^n \quad (6.2)$$

where $\mathbf{\Gamma}_H(.)$ and $\mathbf{\Gamma}_E(.)$ represent the passive dynamics of human and exoskeleton. We assume human and exoskeleton joints are coupled and $\mathbf{q} \in \mathbb{R}^n$ is the joint position of the exoskeleton and human (n : number of joints). $\mathbf{F} \in \mathbb{R}^n$ is the human-exoskeleton interaction force, assumed to be directly measured using a force sensor. $\mathbf{p}(t) \in \mathbb{R}^n$ is the desired trajectory of human (human intention). $\mathbf{r}(t) \in \mathbb{R}^n$ is the exoskeleton reference trajectory that will be adapted in interaction with human dynamics. $\mathbf{e}_H \in \mathbb{R}^n$ is the human error defined as $\mathbf{e}_H = \mathbf{p}(t) - \mathbf{q}$. $\mathbf{u}_H \in \mathbb{R}^n$ is the human applied torque which tries to minimize the human tracking error. Similar to human, exoskeleton tracking error and applied torque is considered as $\mathbf{e}_E = \mathbf{r}(t) - \mathbf{q}$ and $\mathbf{u}_E$, respectively. Exoskeleton reference trajectory ($\mathbf{r}(t)$) is modeled as the sum of initial trajectory ($\mathbf{r}_0(t) \in \mathbb{R}^n$) and a trajectory modification term ($\Delta \in \mathbb{R}^n$). $\mathbf{r}_0(t)$ is a fixed T -periodic function with the period of gait cycle and $\Delta(t)$ is left to be adapted. We parameterize $\Delta(t)$ as a linear combination of basis functions as

$$\mathbf{r}(t) = \Delta(t) + \mathbf{r}_0(t) \quad , \quad \Delta_j(t) = \Theta_j^T \Phi(t) \quad (6.3)$$

where j refers to j th joint. $\Phi(t) \in \mathbb{R}^m$ is a vector of m individual basis functions and $\Theta_j \in \mathbb{R}^m$ is the coefficient vector that is adapted to minimize the desired cost function. It is assumed that the basis functions are T -periodic, sufficiently smooth, and persistently exciting.

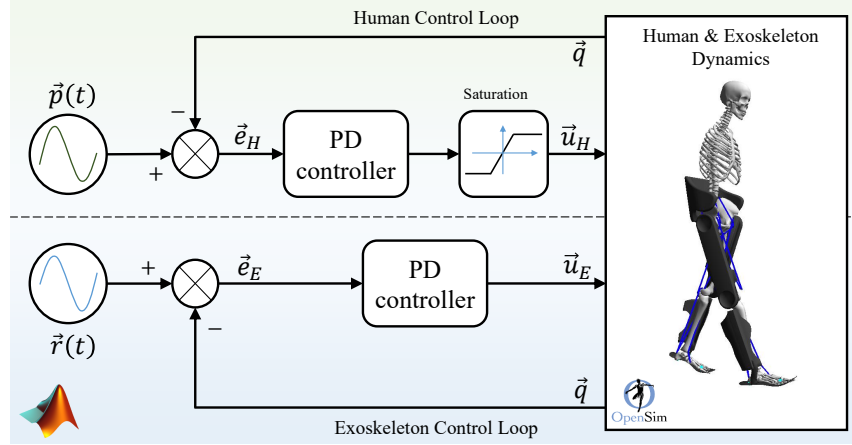


Figure 6.2: Dynamic walking simulator block diagram. The human and exoskeleton controllers are implemented in MATLAB interfacing with the human and exoskeleton models defined in OpenSim along with ground reaction forces. The human tries to control her joint positions ($\mathbf{q}$) on her intended trajectory ($\mathbf{p}$) while the exoskeleton, with no information about the human intended trajectory, tries to minimize the error between the exoskeleton position ($\mathbf{q}$) and reference trajectory ($\mathbf{r}$). The saturation is added to the human control loop to simulate reduced motor capacity.

The proposed adaptation rule updates the bases coefficients at each joint (Θ_j) to minimize our suggested cost function (J) which is the sum of squared interaction force (*cost of interaction force*) and a weighted norm of the trajectory modification term (*cost of modification*), which penalizes deviation from the initial trajectory ($\mathbf{r}_0(t)$).

$$J = \frac{1}{2}(\mathbf{F}^T \mathbf{F} + \Delta^T \boldsymbol{\beta} \Delta) \quad (6.4)$$

$\boldsymbol{\beta} = \text{diag}(\beta_1, \dots, \beta_n)$ is a diagonal and positive definite matrix. For healthy users, we set $\boldsymbol{\beta} \cong \mathbf{0}$ which leads to interaction force minimization; i.e., the exoskeleton would be the follower of human motion. For users with lower motor capacity (e.g., those with *iSCI*) the user's executed movement trajectories are not fully reliable to follow. Therefore, we consider $\beta_j > 0$ to penalize the exploration of reference trajectory at each joint and facilitate maintaining a physiological gait pattern. The increment of β_j depends on the motor capacity of impaired users at each joint; the higher the level of motor impairment, the larger β_j should be.

Bipedal locomotion is generally an underactuated control problem, and its stability is closely associated with the stability of zero dynamics [143]. Any conflict between the human and the exoskeleton controllers can act as a disturbance on the zero dynamics and adversely affect the gait stability and spatiotemporal parameters. In the next section,

we propose a trajectory adaptation method that minimizes the conflict emerging in the form of human-exoskeleton interaction forces (Eq. 6.4) and, therefore, enhances the gait quality. We also investigate the effect of our proposed method on i) gait stability, using the stability margin defined as the minimum distance between the zero moment point (Zero Moment Point (ZMP)) [130] and borders of the extended base of support [96], and on ii) spatiotemporal parameters of gait including the Step Time Asymmetry Index (Step Time Asymmetry Index (STAI)) [101], and minimum Toe Clearance (Minimum Toe Clearance (minTC)) [81], as a low minTC increases the risk of fall.

6.2 Mathematical Analysis

6.2.1 Adaptation Rule Extraction

To extract the adaptation rule for coefficient vector of the j th joint, we apply the gradient descent method to the cost function (Eq. 6.4) as

$$\dot{\Theta}_j = -\frac{1}{2}\epsilon_j \nabla_{\Theta_j} J = -\epsilon_j \left(\frac{\partial F_j}{\partial \Theta_j} F_j + \beta_j \frac{\partial \Delta_j}{\partial \Theta_j} \Delta_j \right) \quad (6.5)$$

where ϵ_j is the adaptation rate. Without loss of generality, in the rest of this section, we follow our analysis at the joint level, therefore, $\Theta, \Phi \in \mathbb{R}^m$, and the rest of the variables are treated as scalars.

Assuming a PD controller at each join of the exoskeleton yields $u_E = K_p e_E + K_d \dot{e}_E$ where K_p and K_d are the proportional and derivative gains, respectively. Therefore, from Eq. 6.2, we obtain $F = K_p e_E + K_d \dot{e}_E - \Gamma_E^j(q, \dot{q}, \ddot{q})$ where Γ_E^j is the j th element of Γ_E (we drop the j superscript from now on). According to Eq. 6.3, the exoskeleton error and its derivative are

$$\begin{aligned} e_E &= r - q = r_0 + \Theta^T \Phi - q \\ \dot{e}_E &= \dot{r} - \dot{q} = \dot{r}_0 + \dot{\Theta}^T \Phi + \Theta^T \dot{\Phi} - \dot{q}. \end{aligned} \quad (6.6)$$

Therefore,

$$\partial F / \partial \Theta = K_p \partial e_E / \partial \Theta + K_d \partial \dot{e}_E / \partial \Theta = K_p \Phi + K_d \dot{\Phi}. \quad (6.7)$$

On the other hand, from Eq. 6.3, we have $\partial \Delta / \partial \Theta = \Phi$. Substituting this expression and Eq. 6.7 into Eq. 6.5, we obtain the adaptation rule as

$$\dot{\Theta} = -\epsilon [\alpha F + \beta \Delta \Phi], \quad \alpha = K_p \Phi + K_d \dot{\Phi}. \quad (6.8)$$

According to the Eq. 6.8, only the user-exoskeleton interaction force (F) is needed to adapt the exoskeleton trajectory.

6.2.2 Convergence Analysis

To investigate the convergence and optimality of the adaptation rule, we substitute $F = K_p e_E + K_d \dot{e}_E - \Gamma_E(q, \dot{q}, \ddot{q})$, $\Delta = \Phi^T \Theta$, and Eq. 6.6 into Eq. 6.8, that yields

$$\begin{aligned} \dot{\Theta} = & -\epsilon[\alpha(K_p \Phi + K_d \dot{\Phi})^T \Theta + \beta \Phi \Phi^T \Theta + K_d \alpha \Phi^T \dot{\Theta} \\ & + \alpha(K_p(r_0 - q) + K_d(\dot{r}_0 - \dot{q}) - \Gamma_E)]. \end{aligned}$$

Performing some algebraic manipulations, the above equation can be rewritten as

$$(\mathbf{I} + \epsilon K_d \alpha \Phi^T) \dot{\Theta} = -\epsilon [\mathbf{A}(t) \Theta - \mathbf{B}(t)] \quad (6.9)$$

$$\mathbf{A}(t) = (\alpha \alpha^T + \beta \Phi \Phi^T) \quad (6.10)$$

$$\mathbf{B}(t) = \alpha (\Gamma_E - K_p(r_0 - q) - K_d(\dot{r}_0 - \dot{q})).$$

Choosing ϵ sufficiently small, we can ignore $\epsilon K_d \alpha \Phi^T$ compared to the identity matrix and simplify the Eq. 6.9 as

$$\dot{\Theta} = -\epsilon [\mathbf{A}(t) \Theta - \mathbf{B}(t)]. \quad (6.11)$$

Since r_0 , $\dot{r}_0$, Φ , and $\dot{\Phi}$ are periodic smooth and bounded functions of time, and q , $\dot{q}$, and $\ddot{q}$ are bounded smooth and almost periodic [34] functions of time, we can compute the averaged adaptation dynamics using *General Averaging Theorem* presented in [57, pp. 413] as

$$\dot{\Theta}_{avg} = -\epsilon \Omega (\Theta_{avg} - \Theta_{avg}^*) \quad (6.12)$$

$$\Omega = \lim_{T \rightarrow \infty} \frac{1}{T} \int_t^{t+T} \mathbf{A}(\tau) d\tau$$

$$\Theta_{avg}^* = \Omega^{-1} \lim_{T \rightarrow \infty} \frac{1}{T} \int_t^{t+T} \mathbf{B}(\tau) d\tau.$$

Since Φ is persistently exciting, and $\alpha \alpha^T$ is positive semi definite, Ω is positive definite [93]. This guarantees the stability and convergence of the average adaptation dynamics (Eq. 6.12) toward $\Theta_{avg} = \Theta_{avg}^*$. The adaptation rule (Eq. 6.8) is thus stable and convergent on average to Θ_{avg}^* .

6.3 Simulator Development

To test the proposed method, we developed a dynamic gait simulator using exoskeleton and human musculoskeletal models in OpenSim. State feedback controllers were implemented within MATLAB (Fig. 6.2). We utilized a 9-DOF lower limb dynamical model in the

sagittal plane as in [21], with the ground reaction force (GRF) formulated using the model from [44, 47]. At each joint, the input torque is the sum of human ($\mathbf{u}_H$) and exoskeleton ($\mathbf{u}_E$) torque. Both human and exoskeleton controllers are assumed as PD controllers that apply torques based on the error from their own joint reference trajectories, which are $\mathbf{p}$ and $\mathbf{r}$, respectively.

6.3.1 Simulator Justification on Healthy Subject Data

The human desired trajectories ($\mathbf{p}$) are fitted to the walking data (at 1.2 m/s) of a healthy adult (provided by OpenSim) with an eight-harmonic Fourier series. For the validation purpose, the exoskeleton model was excluded from simulation and its torques were considered to be zero ($\mathbf{u}_E = \mathbf{0}$). The human controller parameters are reported in Tab. 6.1.

Table 6.1: Exoskeleton and healthy human controller parameters.

Parameter	Exoskeleton			Healthy Human		
	Hip	Knee	Ankle	Hip	Knee	Ankle
Kp [N/deg]	34.9	22.68	34.9	22.68	13.96	31.41
Kd [Ns/deg]	1.04	1.04	0.17	0.52	0.52	0.12
Saturation Level [N.m]	—	—	—	90	85	130

Fig. 6.3 compares joint positions and torques of our simulator with those of real healthy human data. The real and simulated joint positions are almost equivalent with Pearson’s correlation coefficient (R) of ~ 1 . In addition, the torque profiles in all of the joints are comparable to the experimental torques in terms of sign and magnitude. It must be noted that the simulated torques are the result of a PD controller, where the experimental torques are computed by 2D inverse dynamics in OpenSim. The difference between the simulated and the experimental torques is also caused by the imperfection in ground contact modeling and the difference between simulated and real neuromuscular feedback (PD) gains.

Tab. 6.2 compares the R for each joint with two of the well-known biomechanical walking simulators ([38, 138]). Our simulator exhibits a more realistic hip torque profile, while it has a comparable performance at the knee and ankle. Finally, the ground reaction force profiles of our model are similar to the results presented in [38] with R of 0.96 and 0.85 in y and x directions, respectively.

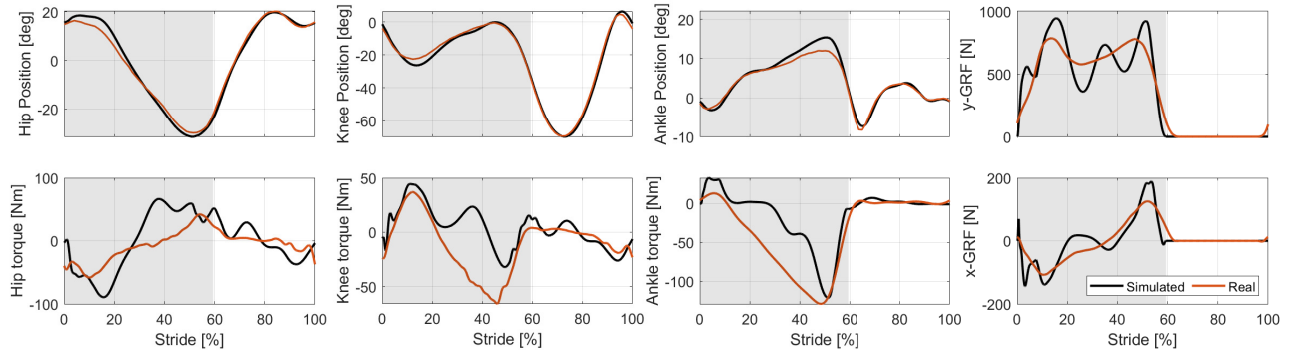


Figure 6.3: The comparison of the simulator and experimental data of a healthy subject (provided in [117]); the gray background indicates the stance phase. The position of the simulator joints closely follows the experimental human trajectory. The torque profiles’ sign and order of magnitude are also close to the ones of human torque profile such that the R -values for hip, knee, and ankle torques are 88%, 45%, and 76%, respectively. In addition, timing and order of magnitude for ground reaction forces are acceptable, and R -values for GRF in y and x directions are 96% and 85%, respectively.

Table 6.2: Simulated joint torques R -value compared to other works.

Joint	Gayer	Van.Noot	Our work
R_{Hip}	0.45	0.53	0.76
R_{Knee}	0.65	0.24	0.45
R_{Ankle}	0.99	0.92	0.88

6.3.2 Simulation of Assisted Walking With an Exoskeleton

Four different human subjects were simulated, one healthy and three with different motor impairments, subjects B, C, and D. To model different motor impairment levels, we considered a torque saturation block, imposing different saturation levels in the human control loop (Fig. 6.2) and decreased the PD gains for the human controller with decreased torque range at more distal joints, which has resemblance to the reduced muscle recruitment in individuals with iSCI, who has ASIA score of B, C and D [52]. Parameters of mid-sever impairment were extracted from [52] indicating that iSCI with ASIA score C can apply between 24% to 36% of the knee extensor and 26% to 38% of the ankle plantar flexor torque that can be generated by healthy subjects. Accordingly, we limited joint torques of our mid-severely impaired subject at 30%, 35%, and 75% of healthy subject maximum joint torque at the ankle, knee, and hip joints, respectively. We assumed the two other impaired subjects to be less and more severely impaired (see Tab. 6.3 for simulated impaired

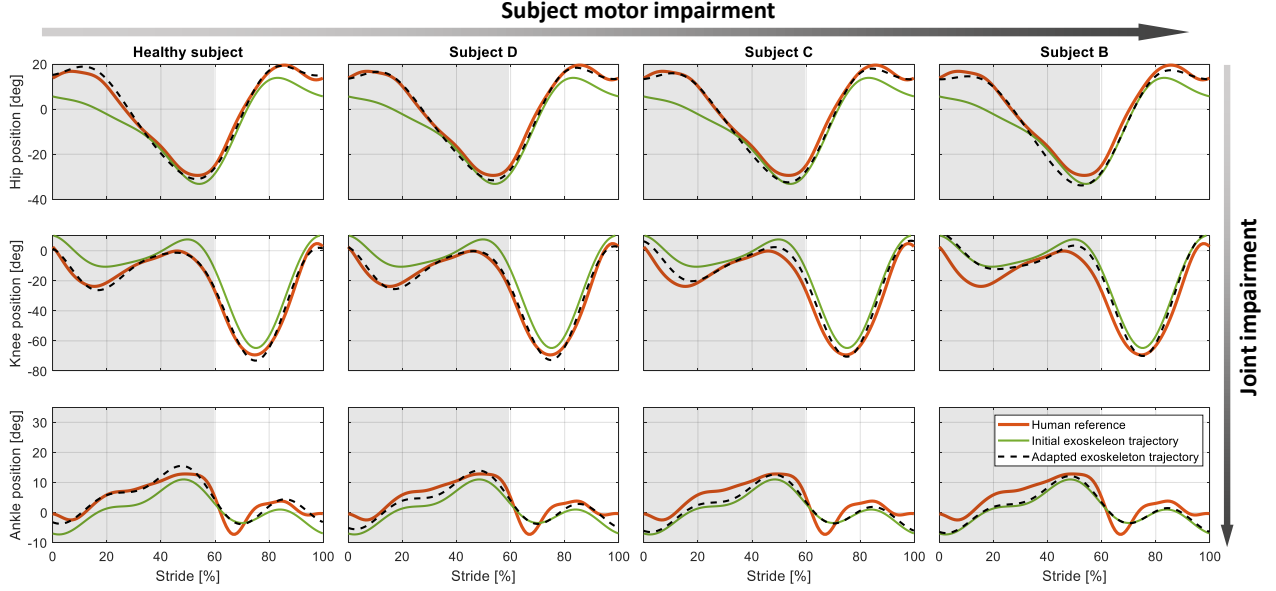


Figure 6.4: Exoskeleton reference trajectory adaptation at the hip, knee, and ankle joints (simulation results). The gray background indicates the stance phase. Each plot includes the human intended trajectory (in red), which is not known by the exoskeleton controller, initial exoskeleton trajectory (in green), and adapted exoskeleton trajectory (dashed lines). Subject B, C, and D are simulated with different reductions in motor capacity to generate the necessary joint torques for predefined intended motion according to [Tab. 6.3](#).

subjects' control parameters).

Table 6.3: Relative controller parameters of impaired subjects compared to healthy subject ([Tab. 6.1](#)).

Subject	Saturation Level [%]			PD Controller Gains [%]			β		
	Hip	Knee	Ankle	Hip	Knee	Ankle	Hip	Knee	Ankle
D	85	60	50	90	80	60	3	91	304
C	75	35	30	80	70	50	6	152	760
B	65	25	25	70	50	30	15	304	1220

Considering the heterogeneity of gait across the subjects, which is more pronounced in case of neurological conditions, and the uncertainty between the intended and executed gait patterns, it is not trivial to have an exoskeleton trajectory with a predefined set of harmonics to exactly match the user's intended trajectory. To benchmark our adaptation rule in a more realistic scenario with the mentioned uncertainties, we chose fewer degrees

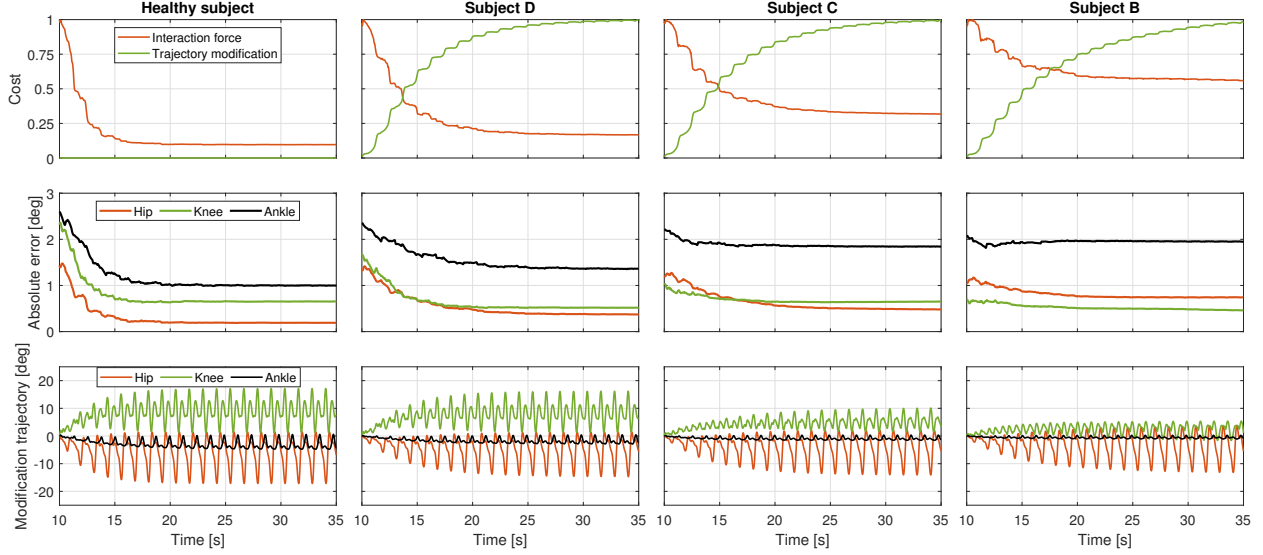


Figure 6.5: The adaptation performance (started at $t = 10s$) comparison in four different subjects. The first row presents the normalized moving average (the window length is $T = 1.23s$) of the trajectory modification and interaction force terms in cost function. The second row illustrates the moving average of the exoskeleton absolute tracking error. Final row is the variations of the modification trajectories in course of adaptation.

of freedom for the exoskeleton trajectory to a maintained mismatch to the user trajectory. Therefore, a three-harmonic Fourier series was fitted to the data of healthy human (provided in [117]) to define $\mathbf{r}_0$. We perturbed the obtained Fourier coefficients so that the resultant exoskeleton initial reference trajectories considerably vary from the human intended trajectories ($\mathbf{p}$), particularly at the hip and ankle. Note that the exoskeleton reference trajectories cannot fully adapt to the human trajectories due to their fewer harmonics, more obvious at the ankle as more oscillations can emerge in comparison to other joints.

We considered the same human trajectories for all the simulated subjects. In practice, however, those trajectories might differ across the users due to different physical characteristics or different impairment levels. With the help of the proposed adaptation method, however, the controller is less sensitive to the mismatch between the initial exoskeleton trajectory and the user preferred gait. We also assumed that the subject was walking on a treadmill. Therefore, there is no mismatch between the frequency of the human intended motion and the exoskeleton's trajectories. In addition, for impaired cases, we have applied a soft constraint to regulate the orientation of the body w.r.t. the world frame; as motor-impaired individuals usually use walkers, walking sticks, and weight compensatory

harnesses to walk. The adaptation rule parameters are as follows: The basis functions (Φ) are the same as Fourier series bases, which are used for initial reference trajectory fitting. ϵ is set to $6.5e-4$, $3.2e-4$, and $1.6e-4$ for the hip, knee, and ankle trajectory adaptation, respectively, so that the basis coefficients (Θ_j) converge to their optimal values within 10 seconds. Adaptation was disabled in the first 10 seconds (8 steps), then enabled and simulations were continued for 60 seconds to ensure gait convergence. We also tuned the β matrix according to the impairment of each subject and the saturation level at each joint, see [Tab. 6.3](#).

6.4 Results and Discussion

[Fig. 6.4](#) compares the adapted, initial, and intended trajectories during one gait cycle in four different simulated subjects. It indicates that, the exoskeleton reference trajectory at the hip joint closely follows the human intended trajectory after the course of adaptation in all subjects regardless of their impairment. The underlying reason is that the hip joint was the least affected joint in simulations. Thus, it can apply the sufficient torque required for the adaptation rule to decode the required trajectory modifications from interaction force. The knee and ankle joints, in contrast, were severely disabled in subjects C and B. As a result, small deviations from the initial trajectories was observed. On the other hand, in the healthy subject and subject D, where those joints are less affected, we observe closer convergence to the human intention due to higher reliance on their performance.

[Fig. 6.5](#) illustrates the cost function, tracking error, and trajectory modification during adaptation. The trajectory modification term and the interaction force costs are convergent while the former is increasing and the latter is decreasing in all cases. Those opposite competing trends provide an equilibrium point for the basis coefficients (Θ^*), which is adjusted (personalized) by β matrix for each subject. Consequently, the interaction force cost decreased in the range of 43%, for severely impaired subject (subject B), to 91%, for the healthy subject.

Moreover, we observed that the healthy subject initially has a comparatively higher tracking error that eventually converges to a lower error since $\beta = \mathbf{0}$ does not penalize the trajectory modification. That is because the adaptation has higher flexibility to explore the parameter space, suggesting the active contribution of simulated user to the gait. As we move toward subject B, this observation becomes less pronounced due to the lower motor capacity of the subjects. The interaction torque was almost proportional to the error and followed the same trend as the ones shown in [Fig. 6.5](#).

[Fig. 6.7](#) demonstrates the converged joint angle and interaction torque patterns in all

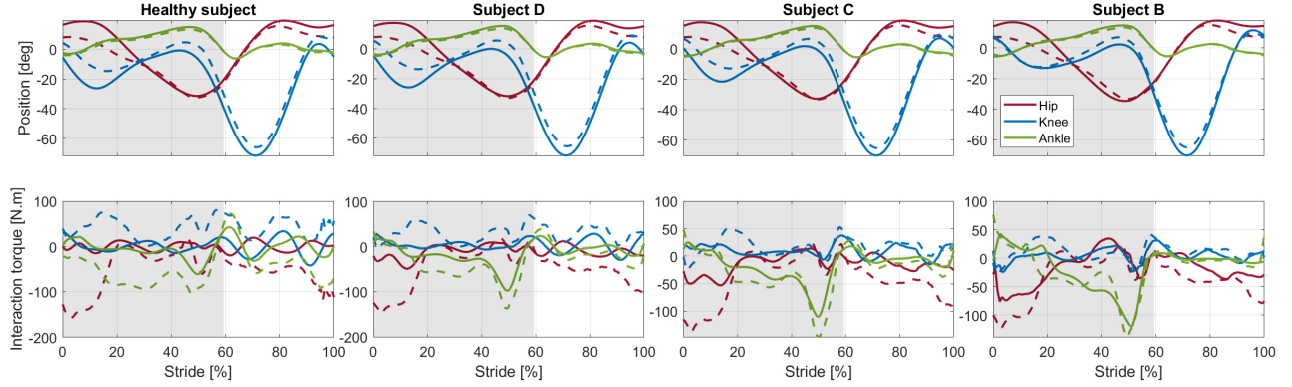


Figure 6.6: Comparison of the joint angles and the interaction torques of the simulated subjects before (dashed lines) and after (solid lines) the adaptation.

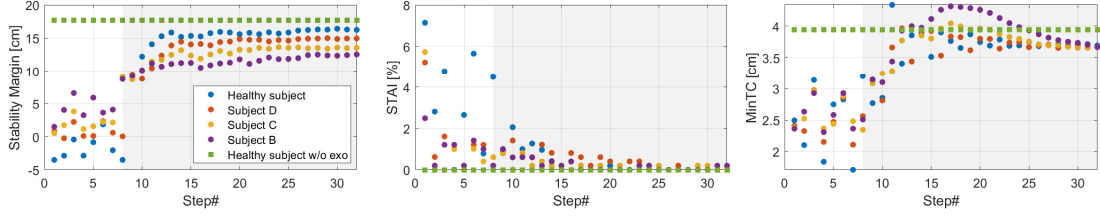


Figure 6.7: Adaptation effect on gait stability (left), step time asymmetry index (middle), and minimum toe clearance (right) across subjects. The gray area denotes the adaptation process started at $t = 10s$ (step #8). Green markers indicate the simulated healthy subject metrics without exoskeleton.

simulated subjects before and after adaptation. Our simulations exhibited larger modification of hip and knee angles at early stance and late swing comparing to the rest of the gait cycle. Adaptation of the exoskeleton reference trajectory leads to a drop in exoskeleton applied torque across all joints (Fig. 6.5) since the exoskeleton torque is the sum of dynamics compensation and interaction torques (based on Eq. 6.2) and while the former is almost fixed the latter is decreased. Besides, the decrease in tracking error indicates that adapted trajectories are more consistent with the dynamics of the human-exoskeleton system.

Fig. 6.7 shows the improved gait stability, step time symmetry, and increased minimum toe clearance, all as a result of trajectory adaptation which decreased the conflict between human and exoskeleton. Stability margin increased in the range of 8cm for the severely impaired subject to more than 18cm for the healthy subject. The healthy subject has the lowest and the highest stability margin before and after the adaption, respectively, while the opposite trend was observed for the severely impaired subject. Moreover, negative

stability margin for the healthy and less severely impaired subjects shows their gait stability is maintained solely due to the harness. Comparison of these results to the stability margin of the healthy subject walking without exoskeleton ($\sim 17.7\text{cm}$) indicates that dependent on the motor capacity of the simulated subjects, the adaptation method resulted in a more natural gait in all cases. Adaptation has also eliminated the gait asymmetry which emerged more in the healthy subject. The decrease in the STAI measure for all subjects indicates more symmetric walking, which is now comparable to the healthy subject walking without exoskeleton. Note that, expected STAI is between 2.36% to 3.6% in real world walking scenario [101], but our simulated healthy subject has an exaggerated symmetric walking. Finally, the minimum toe clearance of the simulated subjects increased by about 40% on average, getting closer to the minTC of the healthy human walking without exoskeleton. The minTC of healthy adults was reported as $2.7 \pm 0.7\text{cm}$ [81], which is close but slightly lower than minTC exhibited in our simulation, i.e. $\sim 3.9\text{cm}$. Maintaining sufficient toe clearance is crucial for impaired individuals to prevent obstacles and reduce the risk of fall.

We assumed that the frequency of human and exoskeleton trajectories are the same. In contrast to the treadmill walking, this assumption is not accurate in overground walking, requiring adaptive identification of the gait frequency [58].

We did not model the adaptation of human desired trajectories. Hence, a large mismatch between the initial trajectories of human and exoskeleton can lead to instability. This is more pronounced in simulation of healthy subject as it can provide high torques to fight back the exoskeleton. In practice, however, human adaptation prevents severe mismatch and triggers the adaptation rule automatically to converge to new trajectories, representing their Nash equilibrium [75].

In this study, the motor impairment was simulated by saturating and weakening joint controllers. We acknowledge that motor impairment can have other aspects which are not modeled here; however, our simulator provides a fair benchmark for testing the proposed method. As a future work, the human controllers will be reimplemented at the muscle level enabling us to simulate more complex impairments such as muscle flaccidity [19] or spasticity [12]. We also plan to implement the proposed adaptation in human experiments.

6.5 Conclusion

We presented an online trajectory adaptation technique based on interaction force measurement with an adjustable capacity to converge to the human intended joint trajectories. We also developed a gait simulator by integrating MATLAB and OpenSim. We applied

the proposed method to simulated healthy and three motor-impaired subjects, with similarities to [iSCI](#) patients with different levels of injury. The simulation results show that we can adapt the exoskeleton reference trajectories to the intended trajectories of healthy subjects. On motor-impaired subjects, the proposed method can restrict the adaptation to guarantee a stable, reliable, and rhythmic gait. Exoskeleton trajectory adaptation also led to considerable improvement in gait stability and spatiotemporal parameters. Limiting joint torques for simulation of different impairment levels is an oversimplification. The assumption of human and exoskeleton joint coordinates being the same is another limitation of this work, ignoring the misalignment and the contact dynamics between the user and the exoskeleton.

Chapter 7

Optimization of Human–Exoskeleton Physical Interaction

This chapter presents an online human-exoskeleton interaction optimization method through the adaptation of the exoskeleton’s desired trajectories. Leveraging gait phase and human-exoskeleton interaction torque estimators, our approach allows seamless assistance adaptation to various walking patterns and speeds, relying solely on kinematic measurements of the exoskeleton. We compared our adaptive controller with a similar non-adaptive controller during self-selected overground walking and treadmill walking at three different speeds ranging from 0.4 to 0.8 m/s. Analysis of data collected from 16 participants during overground walking showed that the adaptive controller significantly decreased the human-user interaction torque at the hip and knee joints by $51.2\% \pm 11.1$ and $63.9\% \pm 29.7$, respectively. The muscular effort also significantly decreased by $21.0\% \pm 34.5$ and $28.1\% \pm 34.6$ at the Bicep Femoris and Rectus Femoris muscles, respectively, while remaining relatively the same in other muscles. Spatiotemporal gait analysis demonstrated an average increased cadence and gait speed by $7.6\% \pm 5.2$ and $10.7\% \pm 8.3$, respectively. This suggests that participants were able to walk faster with similar or lower muscular effort, which can be attributed to trajectory adaptation. Furthermore, the temporal analysis revealed that the emerged trajectories of participants after adaptation better matched to that of walking without the exoskeleton. Additionally, the exoskeleton-applied joint torque exhibited higher harmony with the human natural torques as a result of trajectory adaptation. Our proposed adaptive controller maintained its performance during treadmill walking at different speeds indicating a speed-invariant performance over the non-adaptive controller.

7.1 Methods

7.1.1 Interaction force estimation

An Indego Explorer exoskeleton (ekso Bionics, US) was used in this study. According to [123], we consider the dynamics of the lower-limb exoskeleton, with actuated hips and knees, in the presence of interaction forces and torques with 10 degrees of freedom in the sagittal plane as

$$\mathbf{\Gamma}(\mathbf{x}) = \mathbf{u} \quad (7.1)$$

where $\mathbf{\Gamma} : \mathbb{R}^{17} \rightarrow \mathbb{R}^7$ represents the exoskeleton passive dynamics containing the inertial forces, centrifugal and Coriolis forces, and the forces due to gravity [129]. $\mathbf{x} \in \mathbb{R}^{17}$ is the vector of exoskeleton measurements containing the exoskeleton joint angles and their derivatives, one of the exoskeleton's thigh angle with respect to the vector of gravity, its derivatives as well as its linear acceleration measured using an embedded accelerometer. $\mathbf{u} \in \mathbb{R}^7$ contains the net torques and forces applied to the exoskeleton trunk in the horizontal and vertical directions, and the net torques applied to the exoskeleton hip and knee joints of both legs.

A time-delay neural network with 10 input delays, 4 hidden layers of [50 50 20 7] neurons with *tanh* activation is trained using scaled conjugate gradient backpropagation algorithm and was tested to learn the exoskeleton passive dynamics ($\mathbf{\Gamma}$). This enables us to estimate the net forces and torques being applied to the exoskeleton ($\mathbf{u}$) in real-time. Therefore, at each of the exoskeleton hip and knee joints, we can estimate the interaction torque between the human and the exoskeleton as $f = \tau - u$ where f and u stand for the interaction torque and the exoskeleton motor torque, respectively.

7.1.2 Exoskeleton Controllers

Gait Phase-based Exoskeleton Control

At each joint, we implemented a damped P controller (see Fig. 7.1B) with a stiffness of 1.5 N.m/deg and damping of 0.25 N.m.s/deg as

$$u_E = k_p(r_0 - q) - k_d\dot{q}, \quad (7.2)$$

where q and $\dot{q}$ are the angular position and velocity of the joint and r_0 is the desired joint angles obtained from the user during walking with the exoskeleton in passive mode.

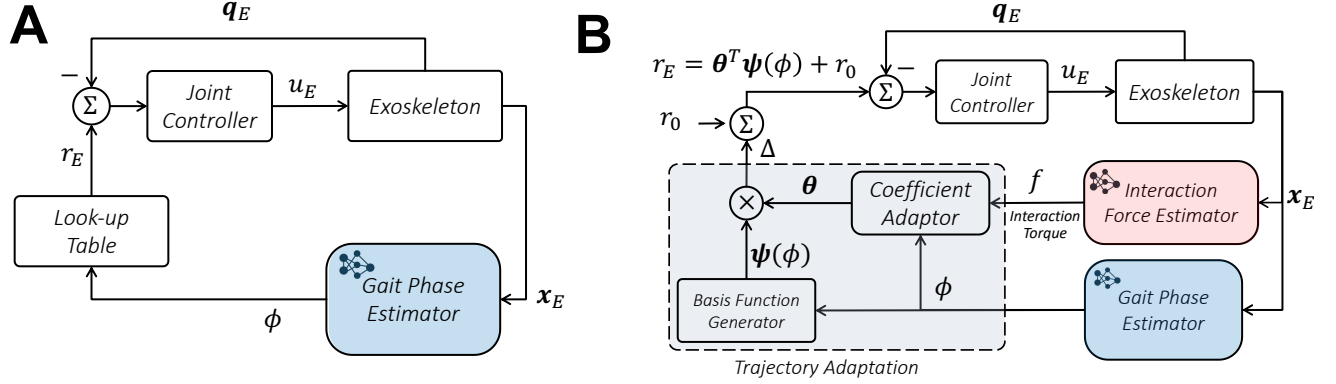


Figure 7.1: **(A)** Block diagram of gait phase-based controller (referred to as non-adaptive controller). Exoskeleton desired trajectories (r_0) are generated as a function of the gait phase using a lookup table obtained during passive walking at slow speed. The gait phase is estimated in real-time using a pre-trained neural network [122]. **(B)** Exoskeleton controller with adaptive trajectory (referred to as adaptive controller). Human-exoskeleton interaction torques are estimated using a pre-trained time-delay neural network according to the exoskeleton measurements ($\mathbf{x}$) [123]. The Fourier coefficients (θ) are then adapted, accordingly, and multiplied by the time-based basis functions containing the first three harmonics of the Fourier series generating the trajectory modification term (Δ). Finally, the exoskeleton desired trajectory r is obtained by the addition of the initial trajectory (r_0) and Δ .

Trajectory Adaptation

To adapt the exoskeleton desired trajectory, we assume the desired trajectory is composed of an initial trajectory obtained walking with the passive exoskeleton (r_0) and a modification term as $r = r_0 + \Delta$. Therefore, the initial trajectory is modified through the adaptation of Δ to minimize the following cost function

$$J = 0.5(f^2 + \beta\Delta^2). \quad (7.3)$$

The weight β is included in the cost function to punish deviations from the initial trajectory; different β s can be applied at different joints of each user according to their motor capacity. For healthy users, we used $\beta = 0.05$ for both joints.

To obtain the adaptation rule, we first parameterize the modification term as $\Delta = \theta^T \psi(\phi)$ where $\theta \in \mathbb{R}^{2n+1}$ is the coefficient vector multiplied to the Fourier basis functions ($\phi \in \mathbb{R}^{2n+1}$) up to the n th harmonic. Using the gradient descent method, the following

update rule is obtained for θ as

$$\dot{\theta} = -\epsilon \frac{\partial J}{\partial \theta} = -\epsilon \left(\frac{\partial J}{\partial f} \times \frac{\partial f}{\partial r} \times \frac{\partial r}{\partial \theta} + \frac{\partial J}{\partial \Delta} \times \frac{\partial \Delta}{\partial \theta} \right) = -\epsilon (f k_p + \beta \Delta) \psi(\phi) \quad (7.4)$$

where $\epsilon = 0.2$ is the step size tuned by trial and error to achieve a smooth yet sufficiently fast convergence. See [124] for the details of adaptation rule extraction, and convergence proof.

7.1.3 Experimental Protocol

The experiment consisted of treadmill and overground walking. The treadmill walking contained three blocks, each involving participants walking first with passive exoskeleton, followed by non-adaptive controller, and finally with an adaptive controller. Within each block, participants walked at three distinct speeds: ultra-slow (0.4 m/s), slow (0.6 m/s), and moderate (0.8 m/s). The order of treadmill speed is designed such that the treadmill speed remains the same in between switching exoskeleton control. The passive and non-adaptive phases of the treadmill walking lasted for 105 strides (35 for each speed). Walking with the adaptive controller was designed to last longer to ensure convergence of the exoskeleton trajectories. For an illustration of the treadmill speed and the order of the controllers applied to the exoskeleton refer to Fig. 7.2.

Performance of the gait phase-based controller with and without adaptation is tested on 16 able-bodied participants (11 males and 5 females, age: 24.5 ± 2.8 years, mass: 65.7 ± 24.1 kg, height: 177.2 ± 10.5 cm). The participants had no known musculoskeletal impairments and they provided informed consent prior to the experiment. The study protocol and procedures were approved by the University of Waterloo Clinical Research Ethics Committee (ORE#41794) and conformed with the Declaration of Helsinki.

The experimental setup comprised a split-belt instrumented treadmill (Bertec, US), with force plates under each belt, providing ground reaction forces (GRF) under each belt, a lower limb exoskeleton (Indego, Ekso Bionics, US) with actuated hip and knee joints, and 14 wireless EMG sensors (Trigno, Delsys, USA). Additionally, four Physilog IMUs (Physilog 6s, Gait Up SA, CH) are employed to measure gait spatiotemporal parameters. The exoskeleton, IMUs, load cells, and EMG sensors have sampling rates of 200 Hz, 128 Hz, 1000 Hz, and 2000 Hz, respectively. Following appropriate skin treatment, EMG sensors were placed on Gluteus Maximus, Biceps Femoris, Rectus Femoris, Vastus Medialis, Medial Gastrocnemius, Soleus, and Tibialis Anterior muscles of each leg. Spatiotemporal gait parameters such as Minimum Toe Clearance (minTC), Maximum Heel Clearance (maxHC),

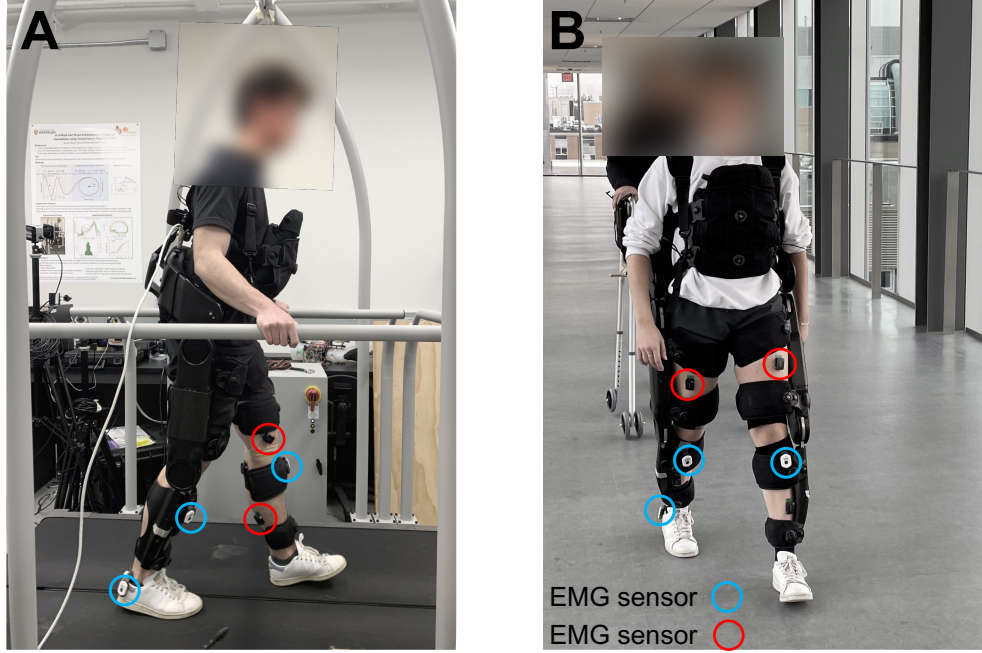


Figure 7.2: Treadmill speed variations during treadmill walking are presented. The experiment begins with 105 strides of walking with a passive exoskeleton, equally distributed among slow (0.6 m/s), ultra-slow (0.4 m/s), and moderate (0.8 m/s) speeds. The passive exoskeleton's trajectory is learned as a function of the gait phase at the slow speed and is used as the initial trajectory (r_0) for subsequent control phases. Following this, a gait phase-based control without trajectory adaptation (non-adaptive) is tested for a similar duration as the passive walking phase. Trajectory adaptation is then activated during slow walking, a condition that persists for 105 strides. Afterward, the treadmill speed is adjusted to moderate and ultra-slow speeds, each maintained for 52 strides, respectively. The adaptive controller is tested over a longer duration than both the non-adaptive and passive scenarios to ensure convergence.

Stance Time Percentage, and Stride Length are computed using the Physilog sensors, as validated in previous studies [11,114]. Fig. 7.3 illustrates the exoskeleton and the placement of the sensors within the experimental setup.

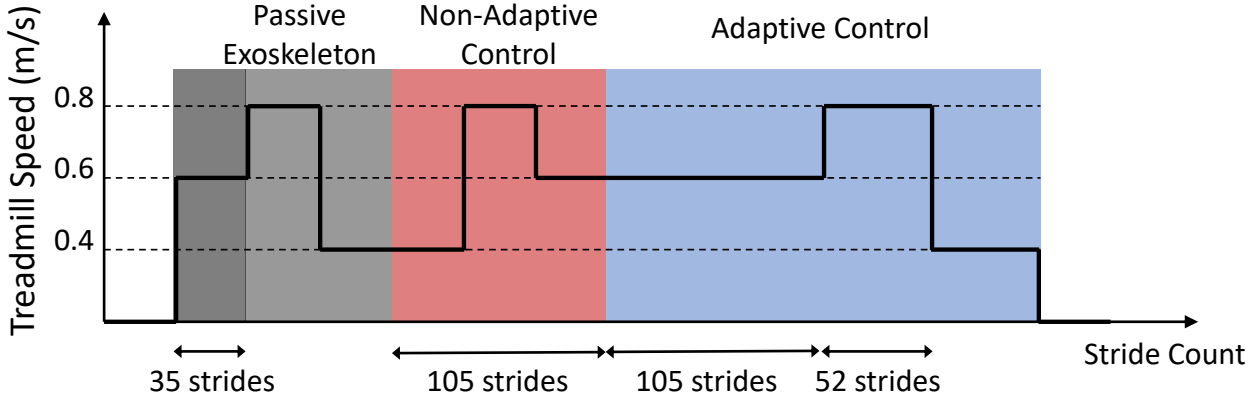


Figure 7.3: (A) A typical participant walking on the treadmill with the exoskeleton while ground reaction forces are measured using force plates under the treadmill belts. Foot kinematics are recorded using Inertial Measurement Units (IMUs) (Physilog 6s, Gait Up SA, CH) attached to the top of both shoes and spatiotemporal parameters are estimated using a Gait Analysis package (GaitUp SA, CH) [67]. Kinematic and muscle activation data are also collected using [EMG](#) sensors at 2KHz and the exoskeleton IMUs and encoders at 200 Hz. (B) Another participant during overground walking, the same experimental setup except the instrumented treadmill.

7.1.4 Data Processing

Muscle Activation

The [EMG](#) data was bandpass filtered, with cutoff frequencies of 5 and 500 Hz. The signal was then full-wave rectified and its envelope was computed by applying a moving average with a window of 100 ms. Each [EMG](#) signal is normalized by its respective maximum voluntary contraction (MVC), computed for each muscle as the maximum measured contraction during walking on the treadmill (maximum across with and without the exoskeleton walking). [18, 102] is computed for each muscle at each stride as

$$\mu_{m,s} = \frac{1}{T_s} \int_{T_s} e_m^2(t) dt,$$

where $e(t)$ is the filtered [EMG](#) signal, T_s is the duration of stride s computed by heel-strike events obtained from vertical GRF measurements, $m \in \{\text{GM, BF, RF, VM, MG, Sol, TA}\}$, is the muscle index. To compare the muscular effort between participants in different

speeds and controllers, we also computed the average muscular effort as

$$\bar{\mu}_{m,c,v} = \sum_{s \in S_{c,v}} \mu_{m,s} \quad (7.5)$$

where $S_{c,v}$ is the set of all strides with speed $v \in \{\text{ultra-slow, slow, moderate}\}$ and controller $c \in \{\text{passive, non-adaptive, adaptive}\}$.

Exoskeleton-Related Metrics

The human-exoskeleton interaction torque is estimated based on Eq. 4.7, given by

$$\mathbf{u}_{int} = \mathbf{\Gamma}(\gamma, \dot{\gamma}, \ddot{\gamma}, \mathbf{a}, \mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) - \mathbf{u}_E. \quad (7.6)$$

The Mean Absolute Interaction Torque (MAIT) is then calculated for each joint as:

$$u_{int,j,s} = \frac{1}{T_s} \int_{T_s} |u_{int,j}(t)| dt,$$

where $j \in \{\text{hip}_{\text{right}}, \text{knee}_{\text{right}}, \text{hip}_{\text{left}}, \text{knee}_{\text{left}}\}$ is the joint index. The Mean Absolute Tracking Error (MATE = $e_{j,s}$) and the Mean Absolute Exoskeleton Torques (MAET = $u_{E,j,s}$) are likewise computed. The average MAIT ($\bar{u}_{int,j,c,v}$), MATE ($\bar{e}_{j,c,v}$), MAET ($\bar{u}_{E,j,c,v}$) are also computed similar to Eq. 7.5.

Statistical Analysis

To identify statistical differences, we initially employed a Friedman test with a significance level of 0.05 to test group-level differences. Following the Friedman test, we conducted pairwise comparisons, between the blocks, using the Wilcoxon signed-rank test. To account for multiple comparisons between the three blocks, we applied the Bonferroni correction.

7.2 Results and Discussions

7.2.1 Overground Walking

Overall comparison

Fig. 7.4A shows the distribution of the average MAIT ($\bar{u}_{int,j,c,v}$) across participants relative to the passive walking. The non-adaptive controller resulted in significantly larger interaction torques at both hip ($+14.5\% \pm 16.4$, $p < 0.005$) and knee ($+62.1\% \pm 32.2$, $p < 0.001$)

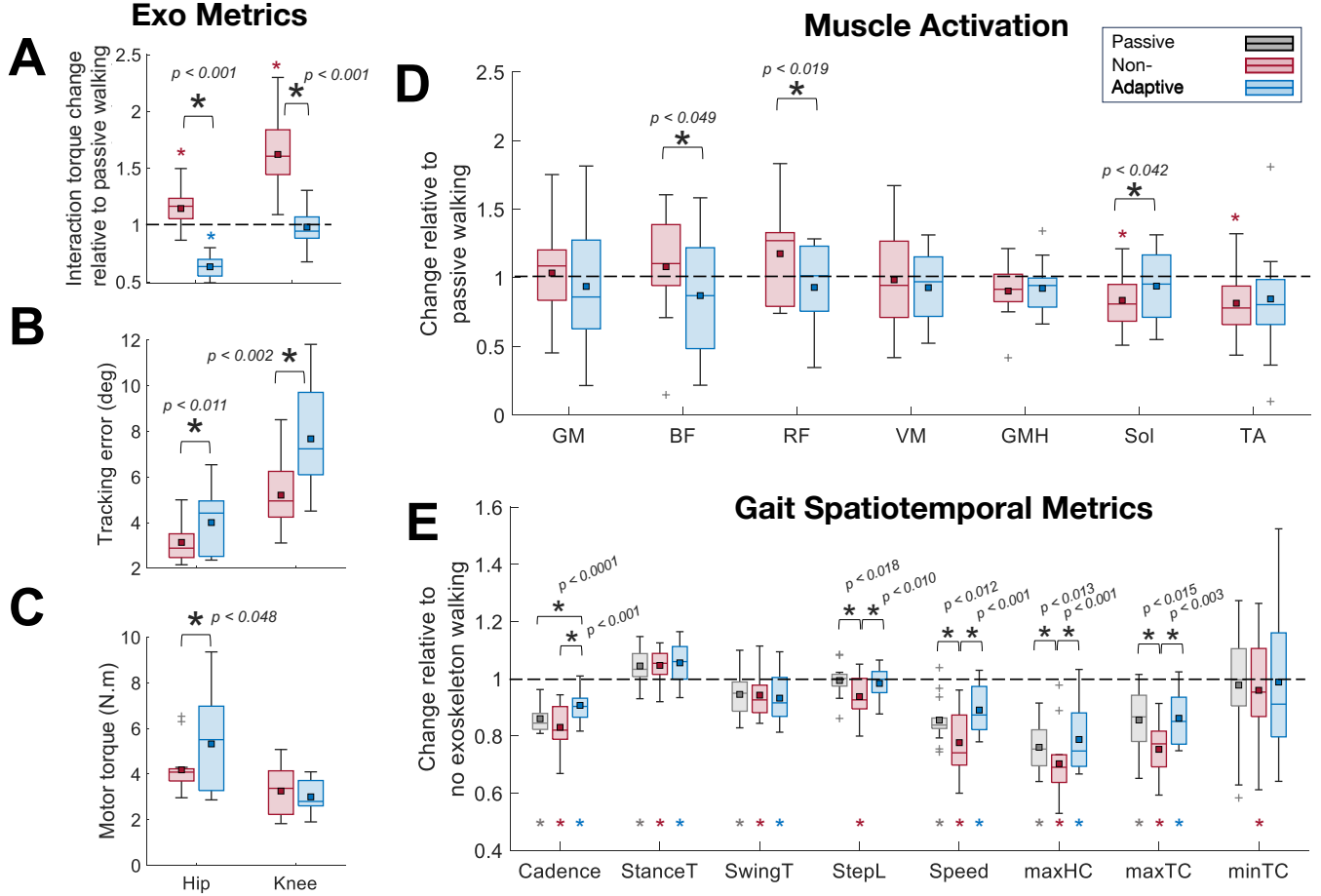


Figure 7.4: (A), (B), and (C) show the distribution of the average [MAIT](#), [MATE](#), and [MAET](#) for the hip and knee joints with non-adaptive and adaptive controllers across participants during overground walking, respectively. (D) shows the muscular effort computed for the measured muscles at the right leg for each controller relative to those of walking with passive exoskeleton. Similarly, (E) illustrates the spatiotemporal gait metrics. Values in (A) and (D) are normalized by the metrics computed during walking with passive exoskeletons as baseline. Values in (E) are normalized over natural walking with no exoskeleton as a baseline. The gray, red, blue, and black asterisks denote significant differences identified in passive-to-baseline, adaptive-to-baseline, and between-controller comparisons, respectively. Squares denote the population mean and crosses indicate the outliers.

joints compared to walking with passive exoskeleton. adaptive controller, on the other hand, has led to a [MAIT](#) decrease by $37.2\% \pm 9.1$ ($p < 0.001$) at the hip joint while the knee joint interaction torque has not significantly changed. Compared to the non-adaptive controller, the adaptive control has led to a significant reduction of the interaction torque both at the hip ($-51.2\% \pm 11.1$, $p < 0.001$) and knee joints ($-63.9\% \pm 29.7$, $p < 0.001$). The accuracy in the interaction torque estimation plays an important role here as at the knee joint, the motor gearbox friction is more dominant compared to the negligible torque due to inertial and Coriolis forces. Due to its semi-random behaviour, static friction identification is less precise at the knee joint decreasing the interaction torque estimation accuracy at the knee joint causing less reduction of interaction torques at the knee joint with the adaptive controller. However, as the adaptive controller is introduced to the user, the interaction torque at the knee joint, which had already increased due to the non-adaptive control, is soon rectified meaning that the interaction torque estimation is accurate enough to resolve excessive interactions at the knee joint.

Similarly, the distribution of the average mean absolute tracking error is presented in [Fig. 7.4B](#). Compared to the non-adaptive controller, tracking error has significantly increased with adaptive control on both hip and knee joints with $0.87^\circ \pm 1.1$ ($p < 0.011$) and $2.46^\circ \pm 2.1$ ($p < 0.002$), respectively. Interestingly, the actual hip trajectory with the adaptive controller at [Fig. 7.5A](#) does not show an abnormal difference from the hip trajectory obtained with the non-adaptive control or passive exoskeleton condition. Therefore, the relatively huge tracking error observed in [Fig. 7.4B](#) is caused by the increase in the range of the desired trajectory. Looking at the controller equation at [Eq. 7.2](#), we notice that the only way the adaptation can directly affect controller output is to modify the desired trajectory. Therefore, the large tracking error in the case of the adaptive control is not necessarily an unfavourable performance measure.

From [Fig. 7.4C](#) we notice that the applied torque at the hip joint is significantly higher ($+1.13 \text{ N.m} \pm 1.64$, $p < 0.048$) with the adaptive controller compared to the non-adaptive control. The lower interaction torque at [Fig. 7.4A](#), moreover, indicates that with adaptation of the desired trajectory, the exoskeleton has more efficiently contributed to the motion at both the hip and the knee joints.

The relative muscular effort is analyzed in [Fig. 7.4D](#). All computed muscular efforts show a slight decrease with the adaptive control compared to walking with passive exoskeleton nevertheless none of these were statistically significant. In Contrast, [GM](#), [BF](#), [RF](#), and [VM](#) muscles show increased muscular effort with the non-adaptive controller. [MG](#), [Sol](#), and [TA](#), on the other hand, show decreased muscular effort with non-adaptive control among which [Sol](#) ($16.5\% \pm 20.3$, $p < 0.021$) and [TA](#) ($18.6\% \pm 23.9$, $p < 0.020$) reductions in muscular effort were significant. Compared to the non-adaptive control, the adaptive

controller has led to $21.0\% \pm 34.5$, and $28.1\% \pm 34.6$ significant reduction in BF ($p < 0.047$) and RF ($p < 0.039$) muscular effort, respectively.

Finally, Fig. 7.4E investigates the gait spatiotemporal metrics. Compared to natural walking, Cadence, speed, maximum heel and toe clearances have significantly dropped by $-17.2\% \pm 7.9$, $-21.3\% \pm 11.6$, $-29.3\% \pm 11.3$, and $24.4\% \pm 9.2$, respectively ($p < 0.001$) during non-adaptive control. Compared to the non-adaptive controller, adaptive control has led to a significant increase in cadence ($+7.6\% \pm 5.2$), speed ($+10.7\% \pm 8.3$), maximum heel ($+8.3\% \pm 6.0$) and toe ($10.6\% \pm 10.2$) clearances, respectively ($p < 0.001$). The increase in gait speed and cadence with the adaptive controller further indicates the efficiency of the exoskeleton assistance as the muscular effort has decreased or remained the same but walking speed has increased. Another unfavorable effect of the non-adaptive controller which is alleviated when switched to the adaptive control is the decrease in heel and toe clearances. Since the user has full control when walking with passive exoskeleton, a closer to 1 value in these measures could be an indicator of a more desired walking in terms of being close to what the participant wants. As a result, the adaptive controller could lead to more desirable walking for the users.

Temporal Analysis with respect to the Gait Phase

Fig. 7.5A shows the average hip and knee joint angles across strides of all participants temporally normalized based on the gait phase. The average hip joint angle with the non-adaptive and adaptive controllers have a Pearson correlation of 0.92 and 0.97, respectively, compared to the natural hip joint angles obtained from [139]. The Pearson correlation coefficient for the knee joint is also obtained as 0.91 and 0.96, respectively. The closer-to-natural joint angles with the adaptive controller may indicate a more natural gait.

Fig. 7.5B represents the average interaction torque across the gait phase being close to zero in most of the gait cycle for the hip joint except at the beginning of the stance and the swing phases. In the case of the knee joint, even though the interaction torque is smaller with the adaptive controller compared to the non-adaptive control, it closely follows the interaction torque during the passive walking which aligns with observations in Fig. 7.4A.

Fig. 7.5C shows the average tracking error with respect to the gait phase. During walking with the passive exoskeleton, the tracking error is close to zero as the exoskeleton is actively learning the used trajectory. Switching to the non-adaptive controller, even though the desired trajectory is the same as what the user maintained during walking with passive control, the tracking error has increased because the exoskeleton applied torques are perceived by the user more as a disturbance rather than assistance. This conclusion

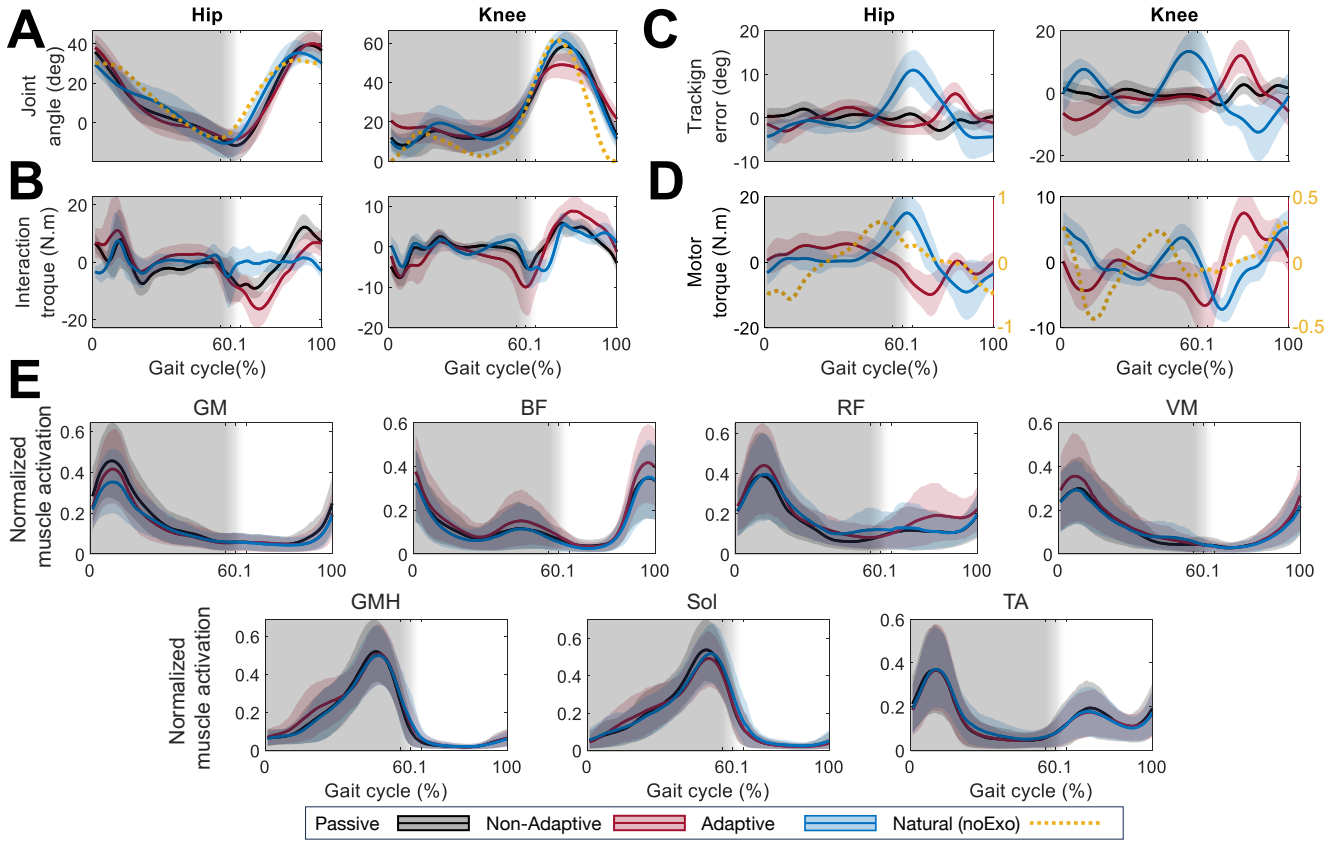


Figure 7.5: Joint angles, interaction torques, tracking error, motor torques, and normalized muscle activation illustrated in (A), (B), (C), (D), and (E), respectively, averaged across participants and strides within each controller and temporally normalized based on gate phase. The shaded area denotes the interquartile range. The gray area also indicates the stance phase.

is supported by the increase in the interaction torques signifying an excessive human-exoskeleton physical disagreement. Switching to the adaptive controller, the tracking error is increased even more. However, the smaller interaction torque along with the closer-to-natural joint trajectories suggest that the increase in tracking error is more toward shaping the exoskeleton assistance in line with the user preference rather than correcting their motion by introducing excessive physical conflict.

Fig. 7.5D shows the average applied motor torques at the hip and knee joints with the non-adaptive and adaptive controllers compared to the physiological joint torques obtained from [139]. The exoskeleton applied torques at the hip joint, when equipped with the

adaptive controller, has almost an opposite sign compared to the non-adaptive controller. The applied torque with the adaptive controller is closer to the human natural torque ($R = 0.65$) than the non-adaptive controller ($R = -0.05$). Notably, natural torque is not the optimal assistive torque as other studies have also reported a lagged version of natural torque to be obtained as local optimum exoskeleton ([10]) torques complying with our findings here. A relatively similar observation is also valid for the knee joint as in this case, both controllers do not show a great match with the natural torque. The adaptive controller applied torque at the knee joint resembles the close-to-toe-off knee flexion torque apparent in natural torque. Both controllers apply a knee extension torque which is not present in the natural torque. The adaptive controller, however, applied this torque slightly later than the toe-off while the non-adaptive controller applied it right at the toe-off. On the other hand, at the early stance phase, the natural torque indicates a relatively large knee extension torque which is slightly present in the non-adaptive controller torque as well, but not in the adaptive controller torque.

Fig. 7.5E shows the muscle activation patterns with respect to the gait phase. In the GM, BF, RF, and VM muscles, the activation during the adaptive controller is smaller than with the non-adaptive controller. Especially the peak of the activation profile is decreased by 17.1%, 12.6%, 8.9%, and 18.5%, respectively. In the GM, the non-adaptive and adaptive controllers have reduced the peak muscle activation by 26.1% and 10.3%, respectively. For the MG, Sol, and TA muscles, the activation is not that different among controllers. Having an unassisted ankle joint may explain invariant Sol and TA activation as these muscles provide torques only on the ankle.

Temporal Analysis with respect to the Stride Count

Fig. 7.6 shows the evolution of computed metrics in Fig. 7.4 in a more detailed manner with respect to the strides during each of the experiment phases across all participants. With the non-adaptive controller, an abrupt change can be observed in muscular efforts in GM, RF, BF, and VM (Fig. 7.6A). As the users become familiar with the controller, their muscular effort decreases gradually as participants try to adapt themselves to the exoskeleton assistance modifying their gait such that they can benefit more from the non-adaptive control. As the controller is switched to adaptive, the muscular effort goes back to their walking-with-passive-exoskeleton level. This is more evident in the case of GM and EF muscles. From the graphs, it is obvious that Adaptation has facilitated the reduction of muscular effort but a longer non-adaptive phase is needed to judge whether muscular effort could have gone back to their level of passive exoskeleton walking without adaptive controller or not. As discussed earlier, MG, Sol, and TA are not affected much by switching

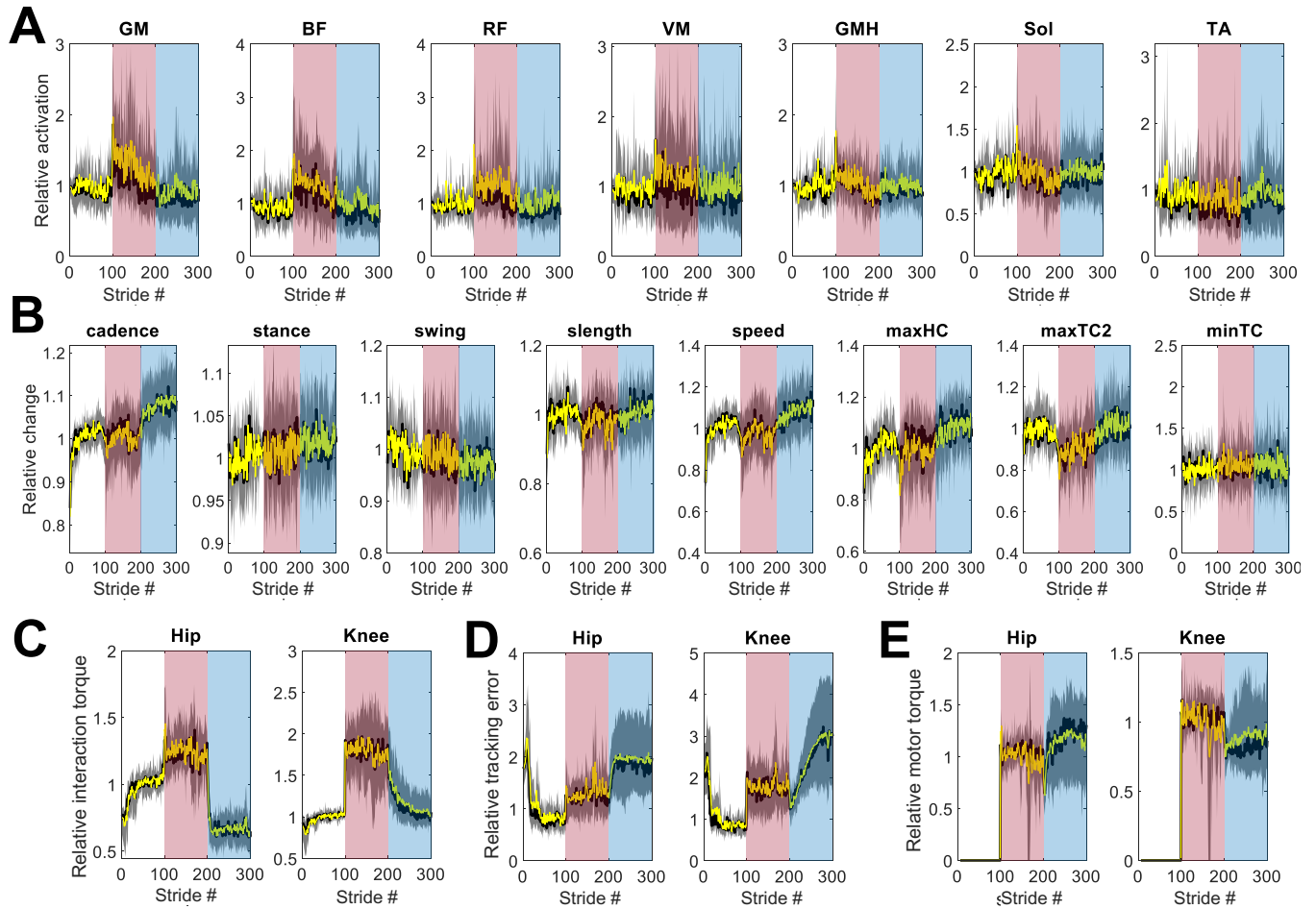


Figure 7.6: Evolution of the muscular effort (**A**), gait spatiotemporal metrics (**B**), **MAIT** (**C**), **MATE** (**D**), and **MAET** (**E**) illustrated for each stride. The black and yellow lines show the mean and median of each metric across participants at each stride. The shaded area represents the interquartile range. Metrics are normalized to their average value during walking with passive exoskeleton except for the motor applied torque which is normalized to its average value during with the non-adaptive controller.

between the controllers.

Fig. 7.6B illustrates the evolution of spatiotemporal gait metrics with respect to the stride number. Walking with the passive controller has the lowest cadence which almost remained the same during the non-adaptive control. With the start of adaptation, cadence increased by almost 10.1% in a few strides. The step length has remained the same within

all three conditions. Therefore, the increase in cadence has translated to gait speed with the adaptive controller. The stance and swing percentages and the minimum toe clearance have remained relatively the same with both controllers. The maximum heel clearance does not show an increase during the non-adaptive control while showing about an 8.7% increase with the adaptive controller. The maximum toe clearance which decreased by about 15% with the non-adaptive controller went back to the same level of walking with passive exoskeleton as a result of trajectory adaptation.

Fig. 7.6C shows the evolution of MAIT relative to its average value during walking with passive exoskeleton. As the non-adaptive control begins, the interaction torque increases by 21.1% on average on the hip joint and remains the same during the whole period of non-adaptive control. With the introduction of the adaptive controller, the interaction torque decreased by 45.6.1% compared to the non-adaptive controller (35.1% compared to walking with passive exoskeleton). Similarly, at the knee joint, the interaction torque is increased by 76.2% with non-adaptive control which is reduced back to the same level of walking with passive exoskeleton during the adaptive control. In terms of steady-state behaviour of tracking error and motor applied torques, the same results presented in Fig. 7.4B, C are observable here as well.

7.2.2 Comparison with Treadmill Walking

Fig. 7.7A compares the change in MAIT with the adaptive controller relative to the non-adaptive control at the hip and the knee joints during ultra-slow (0.4 m/s), slow (0.6 m/s), and moderate walking speeds (0.8 m/s) along with overground walking. The adaptive controller exhibits a consistent performance across different treadmill speeds and overground walking with about a 50% reduction in the average MAIT across all participants. The same observation is true for the knee joint, however, with less reduction in the MAIT. The least reduction at the knee joint is associated with ultra-slow speed walking. Fig. 7.7B similarly investigates the MATE. Compared to the hip joint, MAIT at the knee joint exhibits a higher increase with the adaptive controller compared to the non-adaptive control. Considering the tracking error as a degree of freedom being used for tuning the assistance, the lower increase in the tracking error at the knee joint during the ultra-slow walking speed can explain the low decrease in the interaction torque reduction demonstrated in Fig. 7.7A. With regard to the exoskeleton applied torques, Fig. 7.7C shows that at the hip joint, exoskeleton contribution has dropped with the adaptive controller only in treadmill walking, whereas, in overground walking, the exoskeleton applied torque has increased. This can be associated with the different gait dynamics in treadmill walking compared to overground. During treadmill walking, the treadmill belt's movement reduces the need for

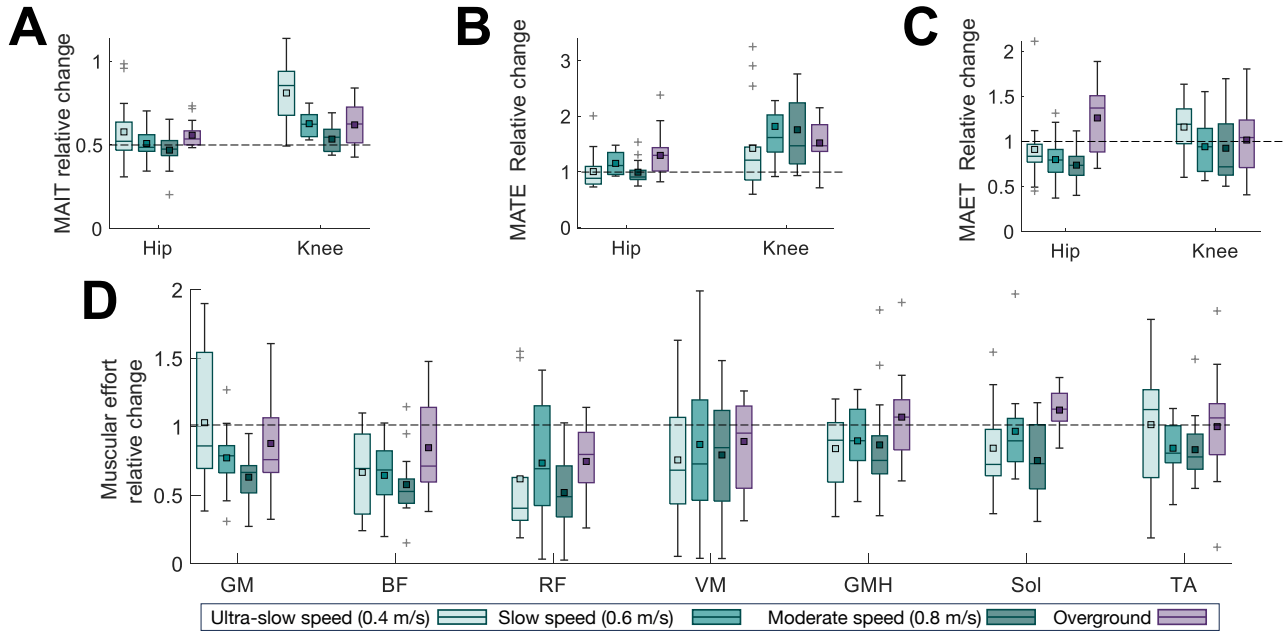


Figure 7.7: The change of [MAIT](#), [MATE](#), [MAET](#), and muscular effort with the adaptive controller relative to the non-adaptive control during treadmill walking at ultra-slow (0.4 m/s), slow (0.6 m/s), moderate (0.8 m/s), and overground walking (at proffered speed) are depicted in (A), (B), (C), and (D), respectively.

forward propulsion decreasing the effort required. The optimum interaction, is therefore, achievable with less exoskeleton contribution to the gait whereas in overground walking, it is all up to the exoskeleton to adjust the assistance and therefore optimizing such assistance can lead to more noticeable changes at the motor applied torques. [Fig. 7.7D](#) illustrated the Muscular effort changes in adaptive control compared to non-adaptive controller. At moderate-speed treadmill walking, the adaptive controller was shown to have the most decrease in muscle activation. This can be related to the fact that in treadmill walking, the gait is assisted by both the exoskeleton and the treadmill. As a result, optimizing the exoskeleton assistance can lead to further easing of the motion. Conversely, this is not the case in the ultra-slow speeds where the adaptive controller performance shows to have higher standard deviation (less consistent) across participants. The ultra-slow walking is different from natural walking in terms of motor control (it is not efficient because the swing leg frequency is far from its natural frequency [126]), the human control over the gait is less consistent and therefore converging to a beneficial exoskeleton behaviour

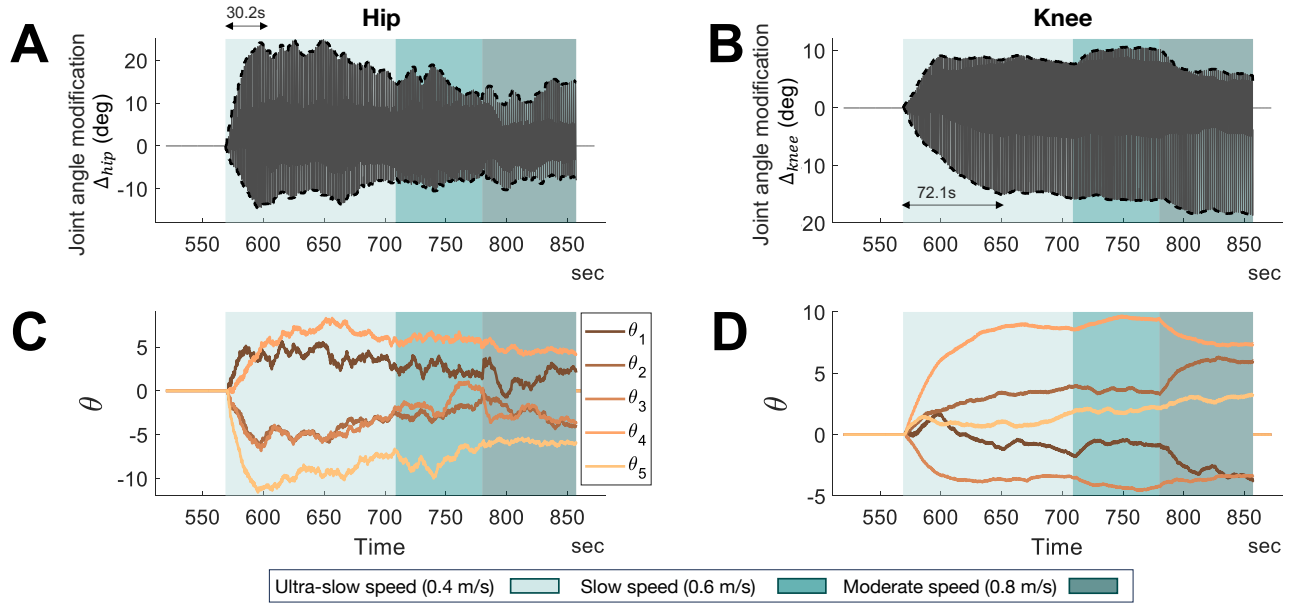


Figure 7.8: Adaptation of the modification trajectories at the hip (A) and the knee (B) joints illustrated for a sample participant during treadmill walking at ultra-slow, slow, and moderate speeds. Similarly, (C) and (D) show the convergence patterns of the Fourier coefficients of each joint.

(assistance) would be more challenging for the exoskeleton.

7.2.3 Convergence Behavior

Fig. 7.6C-E show that convergence of the performance metrics with the adaptive controller is different for the hip and knee joints in terms of convergence speed, even though the same step length is selected for adaptation on both joints. Further analysis of the convergence behaviour is provided in Fig. 7.8 where joint angle modification and adaptation of the Fourier series coefficients are illustrated for both the hip and knee joint of a sample participant. According to the graph, trajectory modification and its associated Fourier coefficients are zero before the start of adaptive control. As the adaptation starts, the modification trajectory (Δ_{hip}) converges to a semi-steady-state pattern. As the adaptation goes on, the hip modification trajectory oscillates as a result of human co-adaptation. It is observed that with fast adaptation, the human-exoskeleton co-adaptation can lead to instability. Therefore, it is necessary that the exoskeleton behaviour changes slowly enough so that the user has enough time to adapt. Moreover, slower exoskeleton adaptation makes

it more predictable from the perspective of the user further facilitating the human adaptation. The hip adaptation speed at the current setting is slow enough to prevent undesired behavior but it can still capture the natural variations in the human walking strategies. At the knee joint, on the other hand, since the magnitude of interaction torque is smaller, the adaption happens at a slower speed. Therefore, human co-adaptation is not reflected at the exoskeleton's desired trajectory immediately and therefore the convergence happens much smoother but less agile at the knee joint.

7.2.4 Interaction Portrait

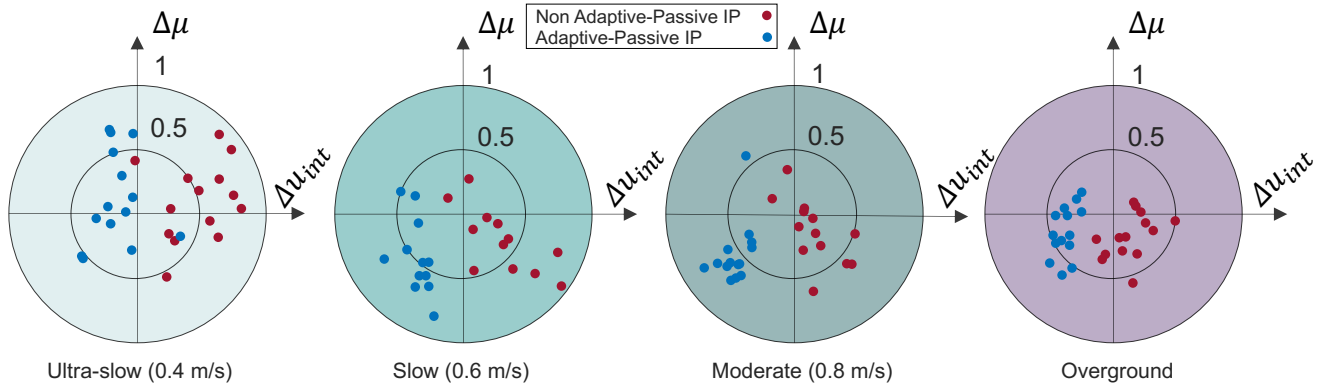


Figure 7.9: Interaction portrait depicted for the non-adaptive and adaptive controllers compared to passive walking with the exoskeleton as a baseline at ultra-slow, slow, and moderate speed walking on the treadmill as well as overground walking with preferred speed. Each point represents one of the participants.

Fig. 7.9 shows the Interaction Portrait analysis for the adaptive and non-adaptive controllers with respect to the passive controller as a baseline during treadmill and overground walking (see chapter 5 for more details). In the case of adaptive controller, most IP points are distributed in the second and third quadrants indicating a decrease in human-exoskeleton physical disagreement compared to the passive passive walking with the exoskeleton. During the ultra-slow treadmill walking and overground walking, the IP points of more participants are located within the second quadrant meaning that compared to the non-adaptive controller, more participants are leading the gait. On the other hand, non-adaptive-passive IP points are mostly distributed in the fourth quadrant denoting that users tend to relinquish control to the exoskeleton rather than taking the lead. The ultra-slow walking speed on the treadmill is an exception where the non-adaptive controller has

led to more human-exoskeleton physical disagreement demonstrated by an increase in total muscular effort and Interaction torques.

7.3 Conclusion

We proposed an online human-exoskeleton interaction optimization method by adaptation of desired exoskeleton trajectories. Leveraging gait phase and human-exoskeleton interaction torque estimators, our approach seamlessly adapts assistance across varying walking patterns and speeds, relying solely on kinematic measurements of the exoskeleton. Comparative analysis against a similar, non-adaptive controller—across both overground and treadmill walking scenarios at speeds between 0.4 to 0.8 m/s—was conducted. Data from 16 participants reveal that our adaptive controller markedly reduced interaction torque at the hip and knee joints by $51.2\% \pm 11.1$ and $63.9\% \pm 29.7$, respectively. Furthermore, muscular effort at the Bicep Femoris and Rectus Femoris muscles significantly declined by $21.0\% \pm 34.5$ and $28.1\% \pm 34.6$, with minimal changes observed in other muscles. Spatiotemporal gait analysis also indicated enhancements in both cadence and gait speed by $7.6\% \pm 5.2$ and $10.7\% \pm 8.3$, suggesting that participants could walk faster, with similar or reduced muscular effort, as a direct consequence of trajectory adaptation. Temporal analysis further demonstrated that post-adaptation trajectories more closely resembled those of walking unaided by an exoskeleton. Additionally, the application of joint torque by the exoskeleton exhibited greater synchrony with human natural torques, underscoring the efficacy of trajectory adaptation. Notably, the proposed adaptive controller maintained consistent performance across various treadmill speeds, highlighting its speed-invariant capabilities relative to the non-adaptive counterpart.

In this study, β was treated more as a regularization factor to ensure stable convergence. However, dealing with people with neuromuscular injuries requires a more careful and systematic tuning procedure for the β . Automatic tuning of β is a future direction of this work enabling the exoskeleton to adjust its level of assistance based on the user performance. Moreover, human passivity is helpful in keeping the human-exoskeleton physical interaction stable. In cases such as clonus, the exoskeleton controller has to avoid certain joint angles and velocity profiles to avoid triggering involuntary reflexes. Considering such constraints in our trajectory adaptation method is another future improvement of this work.

Chapter 8

Conclusion and Outlook

This thesis focused on improving lower limb assistive exoskeletons through the development of novel adaptive control strategies. The core of this work revolved around enhancing the responsiveness of exoskeletons to user movements and intentions, a critical aspect for effective rehabilitation and daily use. By developing adaptive feedback and feedforward controllers based on advanced gait phase and human-exoskeleton interaction torque estimation, this research aimed to make significant strides in the field of robotic rehabilitative technology. In summary, my PhD research contributions are:

1. Developing a robust real-time gait phase estimator.
2. Identifying the dynamics of the Indego exoskeleton regardless of gait phase and estimating the human-exoskeleton interaction torques accordingly.
3. Developing an adaptive feedforward controller that modifies exoskeleton assistance according to the gait phase and user trajectory.
4. Proposing the Interaction Portrait ([IP](#)), allowing co-analysis of interaction torque and muscular effort to distinguish between different human-exoskeleton interaction modes.
5. Developing a simulation environment for the design and testing of exoskeleton controllers using Matlab and Opensim.
6. Proposing, validating, and experimenting a real-time trajectory adaptation method for optimizing human-exoskeleton interaction torques with adjustable adaptation capacity to accommodate a range of user impairments.

A cornerstone of this thesis was the development of a robust gait phase estimator, a tool designed to synchronize the exoskeleton’s assistance with the user’s gait cycle accurately ([chapter 3](#)). Utilizing a time-delay neural network (D67) trained on a rich dataset encompassing various walking speeds and conditions, this model proved effective across a broad spectrum of gait patterns. It achieved an RMSE of 1.74% and 2.35% for treadmill and overground walking, respectively, with the capability to accurately detect heel-strike events—a testament to its precision and potential applicability in real-world settings. Even though this model is trained to maintain its performance in case of a new participant, lack of pathological data in the collected dataset can limit its extension to individuals with severed intramuscular impairments. Parallel to the development of the gait phase estimator, dynamics of the Indego exoskeleton was accurately identified [chapter 4](#). This was achieved through an innovative data collection method that facilitated the measurement of exoskeleton-environment interaction forces. By training various time-delay ANNs on this data, a model was developed that could precisely estimate exoskeleton joint torques and interaction forces, an essential step towards human-exoskeleton interaction torque estimation needed for optimizing the physical interaction between the user and the exoskeleton. Despite its simplicity due to proposing a unified mode for the whole gait cycle, our approach does not support interaction estimation in the presence of ground reaction forces even though the provided formulation can be extended to such scenarios easily.

Significant strides were made in advancing adaptive control strategies for assistive exoskeletons, particularly through the development of two distinct adaptive controllers. One of the adaptive controllers developed is centred on an online trajectory adaptation technique, aimed at minimizing human-exoskeleton interaction torques. This approach is critical for adapting the exoskeleton’s assistance to match the intended joint trajectories of the user, thus accommodating users with varying levels of motor impairment. Through simulation with MATLAB and OpenSim in [chapter 6](#), this controller demonstrated its capacity to adjust reference trajectories to closely align with those of healthy and simulated motor-impaired subjects. The results underscored improvements in gait stability and spatiotemporal parameters, evidencing the potential of this technique in making exoskeleton use more natural and supportive. Building upon this, an online optimization method was introduced in [chapter 7](#) to refine this adaptation process further, utilizing gait phase and interaction torque estimators. Tested against a non-adaptive baseline controller, this enhanced feedback controller significantly reduced interaction torques and muscular effort across key muscles, indicating a more harmonious and less strenuous walking experience for the user.

The adaptive feedforward controller developed in this research ([chapter 5](#)) represents a simple approach to enhancing the functionality of assistive exoskeletons. This controller

learns the user’s trajectory based on the estimated gait phase, capturing the nuances of individual movement patterns. By integrating this learned trajectory with the dynamic model of the exoskeleton, the controller generates feedforward torques that align closely with the user’s natural gait and enhance the overall walking experience.

To evaluate the impact of the developed controller, we introduced the Interaction Portrait (IP) analysis [chapter 5](#). Providing a comprehensive view of the dynamics between the user and the exoskeleton, offering insights into how different control strategies affect user reliance and engagement. Through IP analysis, it was observed that the proposed adaptive feedforward and feedback controllers promote an optimal balance between user effort and mechanical assistance compared to other tested controllers. This balance is crucial for encouraging active participation from the user, an essential element in rehabilitation scenarios and for the long-term efficacy of assistive technologies.

Outlook

Despite the contributions of this research, several areas require further exploration:

- **Further Testing of Gait Phase Estimator:** While the estimator demonstrated high accuracy, additional validation with individuals exhibiting impaired gait patterns is necessary. This would ensure the estimator’s robustness and applicability to a wider range of users.
- **Inclusion of Pathological Gait Data:** Integrating data from individuals with specific gait impairments into the training process of the gait phase estimator could enhance its predictive accuracy and make the adaptive controllers more effective for users with varied mobility challenges.
- **Refinement of Adaptive Controllers:** Future work should focus on refining the adaptive feedback controllers to include automatic tuning of parameters such as the adaptation capacity. This would allow the controllers to more precisely adjust the level of assistance based on the user’s real-time performance and rehabilitation progress.
- **Expansion to Diverse Walking Scenarios:** Testing the developed controllers in a broader array of walking environments and conditions would provide deeper insights into their adaptability and effectiveness in real-world applications.
- **Application to Other Mobility Aids:** Extending the research to encompass other types of mobility aids could broaden the impact of these findings, offering new solutions

to enhance mobility and independence for a wider range of individuals with mobility impairments.

- **Inclusion of Human Cost Function:** Human behavior can be modeled as the result of an optimization process. Identifying and incorporating the human cost function in controller design is essential for a more harmonious assistance strategy. This approach also requires developing stochastic models to account for natural human variability.

In summary, this thesis contributes to the field of rehabilitative exoskeletons by developing advanced control strategies aimed at improving user-exoskeleton interaction. While it lays a solid foundation for future work in this area, it also highlights the need for continued research to fully realize the potential of these technologies in enhancing the lives of individuals with [SCI](#).

References

- [1] Nima Akhlaghi, Clayton A Baker, Mohamed Lahlou, Hozaifah Zafar, Karthik G Murthy, Huzefa S Rangwala, Jana Kosecka, Wilsaan M Joiner, Joseph J Pancrazio, and Siddhartha Sikdar. Real-time classification of hand motions using ultrasound imaging of forearm muscles. *IEEE Transactions on Biomedical Engineering*, 63(8):1687–1698, 2015.
- [2] Daisuke Aoyagi, Wade E Ichinose, Susan J Harkema, David J Reinkensmeyer, and James E Bobrow. A robot and control algorithm that can synchronously assist in naturalistic motion during body-weight-supported gait training following neurologic injury. *IEEE Transactions on neural systems and rehabilitation engineering*, 15(3):387–400, 2007.
- [3] Arash Arami, Edwin van Asseldonk, Herman van der Kooij, and Etienne Burdet. A clustering-based approach to identify joint impedance during walking. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(8):1808–1816, 2020.
- [4] Hamed Jabbari Asl and Tatsuo Narikiyo. An assistive control strategy for rehabilitation robots using velocity field and force field. In *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*, pages 790–795. IEEE, 2019.
- [5] Hamed Jabbari Asl, Tatsuo Narikiyo, and Michihiro Kawanishi. An assist-as-needed velocity field control scheme for rehabilitation robots. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 3322–3327. IEEE, 2018.
- [6] Hamed Jabbari Asl, Masashi Yamashita, Tatsuo Narikiyo, and Michihiro Kawanishi. Field-based assist-as-needed control schemes for rehabilitation robots. *IEEE/ASME Transactions on Mechatronics*, 25:2100–2111, 2020.

- [7] Ajay Bakshi, Corey Hunter, Sharon Swanger, Angelo Lepore, and Itzhak Fischer. Minimally invasive delivery of stem cells for spinal cord injury: advantages of the lumbar puncture technique. *Journal of Neurosurgery: Spine*, 1(3):330–337, 2004.
- [8] Sai K Banala, Suni K Agrawal, and John P Scholz. Active leg exoskeleton (alex) for gait rehabilitation of motor-impaired patients. In *2007 IEEE 10th international conference on rehabilitation robotics*, pages 401–407. IEEE, 2007.
- [9] Darryl C Baptiste and Michael G Fehlings. Pharmacological approaches to repair the injured spinal cord. *Journal of neurotrauma*, 23(3-4):318–334, 2006.
- [10] Gwendolyn M. Bryan, Patrick W. Franks, Seungmoon Song, Ricardo Reyes, Meghan P. O’Donovan, Karen N. Gregorczyk, and Steven H. Collins. Optimized hip-knee-ankle exoskeleton assistance reduces the metabolic cost of walking with worn loads. *Journal of Neuroengineering and Rehabilitation*, 18:1–13, 2021.
- [11] K Carroll, RA Kennedy, V Koutoulas, M Bui, and CM Kraan. Validation of shoe-worn gait up physilog® 5 wearable inertial sensors in adolescents. *Gait & Posture*, 91:19–25, 2022.
- [12] Yesung Cha and Arash Arami. Quantitative modeling of spasticity for clinical assessment, treatment and rehabilitation. *Sensors*, 20(18):5046, 2020.
- [13] Lingling Chen, Chao Wang, Xiaowei Song, Jie Wang, Tengyu Zhang, and Xue Li. Dynamic trajectory adjustment of lower limb exoskeleton in swing phase based on impedance control strategy. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 234(10):1120–1132, 2020.
- [14] Erina Cho, Richard Chen, Lukas-Karim Merhi, Zhen Xiao, Brittany Pousett, and Carlo Menon. Force myography to control robotic upper extremity prostheses: a feasibility study. *Frontiers in bioengineering and biotechnology*, 4:18, 2016.
- [15] Wonseok Choi, Wonseok Yang, Jaeyoung Na, Giuk Lee, and Woonchul Nam. Feature optimization for gait phase estimation with a genetic algorithm and bayesian optimization. *Applied Sciences*, 11(19):8940, 2021.
- [16] Jennifer L Collinger, Stephen Foldes, Tim M Bruns, Brian Wodlinger, Robert Gaunt, and Douglas J Weber. Neuroprosthetic technology for individuals with spinal cord injury. *The journal of spinal cord medicine*, 36(4):258–272, 2013.

- [17] Brecht Corteville, Erwin Aertbeliën, Herman Bruyninckx, Joris De Schutter, and Hendrik Van Brussel. Human-inspired robot assistant for fast point-to-point movements. In *Proceedings 2007 IEEE International Conference on Robotics and Automation*, pages 3639–3644. IEEE, 2007.
- [18] Roy D. Crowninshield and Richard A. Brand. A physiologically based criterion of muscle force prediction in locomotion. *Journal of Biomechanics*, 14:793–801, 1981.
- [19] Janis J Daly, Robert L Ruff, Saidi Osman, and Jennifer J Hull. Response of prolonged flaccid paralysis to fns rehabilitation techniques. *Disability and rehabilitation*, 22(12):565–573, 2000.
- [20] Stefano Marco Maria De Rossi, Nicola Vitiello, Tommaso Lenzi, Renaud Ronsse, Bram Koopman, Alessandro Persichetti, Fabrizio Vecchi, Auke Jan Ijspeert, Herman Van der Kooij, and Maria Chiara Carrozza. Sensing pressure distribution on a lower-limb exoskeleton physical human-machine interface. *Sensors*, 11(1):207–227, 2010.
- [21] Scott L Delp, J Peter Loan, Melissa G Hoy, Felix E Zajac, Eric L Topp, and Joseph M Rosen. An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures. *IEEE Transactions on Biomedical engineering*, 37(8):757–767, 1990.
- [22] Yuemin Ding, Abba J Kassin, and Weihong Pan. Neural plasticity after spinal cord injury. *Current pharmaceutical design*, 11(11):1441–1450, 2005.
- [23] Hannah Dinovitzer, Mohammad Shushtari, and Arash Arami. Accurate real-time joint torque estimation for dynamic prediction of human locomotion. *IEEE Transactions on Biomedical Engineering*, 70:2289–2297, 2023.
- [24] Hannah Dinovitzer, Mohammad Shushtari, and Arash Arami. Feedforward control of lower limb exoskeletons: which torque profile should we use? *IEEE Robotics and Automation Letters*, 2023.
- [25] G. Dominijanni, D. L. Pinheiro, L. Pollina, B. Orset, M. Gini, E. Anselmino, C. Pierella, J. Olivier, S. Shokur, and S. Micera. Human motor augmentation with an extra robotic arm without functional interference. *Science Robotics*, 8, 2023.
- [26] Guillaume Durandau, Wolfgang F. Rampeltshammer, Herman van der Kooij, and Massimo Sartori. Neuromechanical model-based adaptive control of bilateral ankle exoskeletons: biological joint torque and electromyogram reduction across walking conditions. *IEEE Transactions on Robotics*, 38:1380–1394, 2022.

- [27] Alexander Duschau-Wicke, Joachim Von Zitzewitz, Andrea Caprez, Lars Lunenburger, and Robert Riener. Path control: a method for patient-cooperative robot-aided gait rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 18(1):38–48, 2009.
- [28] Florin Dzeladini, Amy R Wu, Daniel Renjewski, Arash Arami, Etienne Burdet, Edwin van Asseldonk, Herman van der Kooij, and Auke J Ijspeert. Effects of a neuromuscular controller on a powered ankle exoskeleton during human walking. In *2016 6th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, pages 617–622. Ieee, 2016.
- [29] Jeremy L Emken, Raul Benitez, and David J Reinkensmeyer. Human-robot cooperative movement training: learning a novel sensory motor transformation during walking with robotic assistance-as-needed. *Journal of neuroengineering and rehabilitation*, 4(1):8, 2007.
- [30] Jeremy L Emken, James E Bobrow, and David J Reinkensmeyer. Robotic movement training as an optimization problem: designing a controller that assists only as needed. In *9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005.*, pages 307–312. IEEE, 2005.
- [31] Jeremy L Emken, Susan J Harkema, Janell A Beres-Jones, Christie K Ferreira, and David J Reinkensmeyer. Feasibility of manual teach-and-replay and continuous impedance shaping for robotic locomotor training following spinal cord injury. *IEEE Transactions on Biomedical Engineering*, 55(1):322–334, 2007.
- [32] Mungai M. Eva and Jessy W. Grizzle. Feedback control design for robust comfortable sit-to-stand motions of 3d lower-limb exoskeletons. *IEEE Access*, 9:122–161., 2020.
- [33] Ryan J Farris, Hugo A Quintero, Spencer A Murray, Kevin H Ha, Clare Hartigan, and Michael Goldfarb. A preliminary assessment of legged mobility provided by a lower limb exoskeleton for persons with paraplegia. *IEEE Transactions on neural systems and rehabilitation engineering*, 22(3):482–490, 2013.
- [34] Arlington M Fink. *Almost periodic differential equations*, volume 377. Springer, 2006.
- [35] Christian Fleischer and Günter Hommel. A human–exoskeleton interface utilizing electromyography. *IEEE Transactions on Robotics*, 24(4):872–882, 2008.
- [36] Patrick W. Franks, Gwendolyn M. Bryan, Russell M. Martin, Ricardo Reyes, Ava C. Lakmazaheri, and Steven H. Collins. Comparing optimized exoskeleton assistance of

- the hip, knee, and ankle in single and multi-joint configurations. *Wearable Technologies*, 2:e16, 2021.
- [37] Shuzhi Sam Ge, Yanan Li, and Hongsheng He. Neural-network-based human intention estimation for physical human-robot interaction. In *2011 8th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI)*, pages 390–395. IEEE, 2011.
 - [38] Hartmut Geyer and Hugh Herr. A muscle-reflex model that encodes principles of legged mechanics produces human walking dynamics and muscle activities. *IEEE Transactions on neural systems and rehabilitation engineering*, 18(3):263–273, 2010.
 - [39] Justin Ghan and Hami Kazerooni. System identification for the berkeley lower extremity exoskeleton (bleex). In *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, pages 3477–3484. IEEE, 2006.
 - [40] Michael A Goodrich, Alan C Schultz, et al. Human–robot interaction: a survey. *Foundations and Trends® in Human–Computer Interaction*, 1(3):203–275, 2008.
 - [41] Kai Gui, Honghai Liu, and Dingguo Zhang. Toward multimodal human–robot interaction to enhance active participation of users in gait rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(11):2054–2066, 2017.
 - [42] Kai Gui, Honghai Liu, and Dingguo Zhang. A practical and adaptive method to achieve emg-based torque estimation for a robotic exoskeleton. *IEEE/ASME Transactions on Mechatronics*, 24(2):483–494, 2019.
 - [43] Lisa A Harvey. Physiotherapy rehabilitation for people with spinal cord injuries. *Journal of physiotherapy*, 62(1):4–11, 2016.
 - [44] Heinrich Hertz. On the contact of elastic solids. *Z. Reine Angew. Mathematik*, 92:156–171, 1881.
 - [45] Neville Hogan. Impedance control: An approach to manipulation: Part ii—implementation. 1985.
 - [46] Woolim Hong, Namita Anil Kumar, and Pilwon Hur. A phase-shifting based human gait phase estimation for powered transfemoral prostheses. *IEEE Robotics and Automation Letters*, 6(3):5113–5120, 2021.
 - [47] Kenneth H Hunt and Frank R Erskine Crossley. Coefficient of restitution interpreted as damping in vibroimpact. 1975.

- [48] K. A. Ingraham, C. D. Remy, and E. J. Rouse. The role of user preference in the customized control of robotic exoskeletons. *Science robotics*, 7, 2022.
- [49] Jeffrey F Israel, Donielle D Campbell, Jennifer H Kahn, and T George Hornby. Metabolic costs and muscle activity patterns during robotic-and therapist-assisted treadmill walking in individuals with incomplete spinal cord injury. *Physical therapy*, 86(11):1466–1478, 2006.
- [50] Rachel W. Jackson and Steven H. Collins. Heuristic-based ankle exoskeleton control for co-adaptive assistance of human locomotion. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27:2059–2069, 2019.
- [51] Nathanaël Jarrassé, Themistoklis Charalambous, and Etienne Burdet. A framework to describe, analyze and generate interactive motor behaviors. *PloS one*, 7(11):e49945, 2012.
- [52] A Jayaraman, CM Gregory, M Bowden, JE Stevens, P Shah, AL Behrman, and K Vandenborne. Lower extremity skeletal muscle function in persons with incomplete spinal cord injury. *Spinal cord*, 44(11):680–687, 2006.
- [53] Saso Jezernik, Gery Colombo, and Manfred Morari. Automatic gait-pattern adaptation algorithms for rehabilitation with a 4-dof robotic orthosis. *IEEE Transactions on Robotics and Automation*, 20(3):574–582, 2004.
- [54] Inseung Kang, Pratik Kunapuli, and Aaron J Young. Real-time neural network-based gait phase estimation using a robotic hip exoskeleton. *IEEE Transactions on Medical Robotics and Bionics*, 2(1):28–37, 2019.
- [55] Inseung Kang, Dean D Molinaro, Srijan Duggal, Yanrong Chen, Pratik Kunapuli, and Aaron J Young. Real-time gait phase estimation for robotic hip exoskeleton control during multimodal locomotion. *IEEE Robotics and Automation Letters*, 6(2):3491–3497, 2021.
- [56] Seiichiro Katsura, Yuichi Matsumoto, and Kouhei Ohnishi. Modeling of force sensing and validation of disturbance observer for force control. *IEEE Transactions on industrial electronics*, 54(1):530–538, 2007.
- [57] Hassan K. Khalil. *Nonlinear systems*. Prentice hall Upper Saddle River, 2002.
- [58] Mahdi Khoramshahi, Rezvan Nasiri, Mohammad Shushtari, Auke Jan Ijspeert, and Majid Nili Ahmadabadi. Adaptive natural oscillator to exploit natural dynamics for energy efficiency. *Robotics and Autonomous Systems*, 97:51–60, 2017.

- [59] Kazuo Kiguchi and Yoshiaki Hayashi. An emg-based control for an upper-limb power-assist exoskeleton robot. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 42(4):1064–1071, 2012.
- [60] Hermano Igo Krebs, Jerome Joseph Palazzolo, Laura Dipietro, Mark Ferraro, Jennifer Krol, Keren Rannekleiv, Bruce T Volpe, and Neville Hogan. Rehabilitation robotics: Performance-based progressive robot-assisted therapy. *Autonomous robots*, 15:7–20, 2003.
- [61] Emek Barış Küçükatabak, Yue Wen, Sangjoon J. Kim, Matthew Short, Daniel Ludvig, Levi Hargrove, Eric Perreault, Kevin Lynch, and Jose Pons. Haptic transparency and interaction force control for a lower-limb exoskeleton. *IEEE Transactions on Robotics*, 2024.
- [62] Colin Lea, Michael D Flynn, Rene Vidal, Austin Reiter, and Gregory D Hager. Temporal convolutional networks for action segmentation and detection. In *proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 156–165, 2017.
- [63] Hyunglae Lee, Elliott J Rouse, and Hermano Igo Krebs. Summary of human ankle mechanical impedance during walking. *IEEE journal of translational engineering in health and medicine*, 4:1–7, 2016.
- [64] Jinwon Lee, Woolim Hong, and Pilwon Hur. Continuous gait phase estimation using lstm for robotic transfemoral prosthesis across walking speeds. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 29:1470–1477, 2021.
- [65] Sangheum Lee, Harin Kim, Hyeonjun Park, Taeyang Gwon, and Donghan Kim. Real-time joint torque estimation on embedded system using emg and artificial neural network for exoskeleton robot. In *2020 Fourth IEEE International Conference on Robotic Computing (IRC)*, pages 480–484. IEEE, 2020.
- [66] U. H. Lee, V. S. Shetty, P. W. Franks, J. Tan, G. Evangelopoulos, S. Ha, and E. J. Rouse. User preference optimization for control of ankle exoskeletons using sample efficient active learning. *Science Robotics*, 8, 2023.
- [67] Nina Lefeber, Marc Degelaen, Chris Truylers, Iwona Safin, and David Beckwée. Validity and reproducibility of inertial physilog sensors for spatiotemporal gait analysis in patients with stroke. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(9):1865–1874, 2019.

- [68] Tommaso Lenzi, Maria Chiara Carrozza, and Sunil K Agrawal. Powered hip exoskeletons can reduce the user’s hip and ankle muscle activations during walking. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 21(6):938–948, 2013.
- [69] Tommaso Lenzi, Stefano Marco Maria De Rossi, Nicola Vitiello, and Maria Chiara Carrozza. Intention-based emg control for powered exoskeletons. *IEEE transactions on biomedical engineering*, 59(8):2180–2190, 2012.
- [70] Eric C Leuthardt, Gerwin Schalk, Jonathan R Wolpaw, Jeffrey G Ojemann, and Daniel W Moran. A brain–computer interface using electrocorticographic signals in humans. *Journal of neural engineering*, 1(2):63, 2004.
- [71] Cara L Lewis and Daniel P Ferris. Invariant hip moment pattern while walking with a robotic hip exoskeleton. *Journal of biomechanics*, 44(5):789–793, 2011.
- [72] Jinglei Li and Perry Y Li. Passive velocity field control (pvfc) approach to robot force control and contour following. In *Proc. of the Japan/USA Symposium on Flexible Automation*. Citeseer, 2000.
- [73] Yanan Li, Gowrishankar Ganesh, Nathanaël Jarrassé, Sami Haddadin, Alin Albu-Schaeffer, and Etienne Burdet. Force, impedance, and trajectory learning for contact tooling and haptic identification. *IEEE Transactions on Robotics*, 34(5):1170–1182, 2018.
- [74] Yanan Li and Shuzhi Sam Ge. Human–robot collaboration based on motion intention estimation. *IEEE/ASME Transactions on Mechatronics*, 19(3):1007–1014, 2013.
- [75] Yanan Li, Keng Peng Tee, Wei Liang Chan, Rui Yan, Yuanwei Chua, and Dilip Kumar Limbu. Continuous role adaptation for human–robot shared control. *IEEE Transactions on Robotics*, 31(3):672–681, 2015.
- [76] Chiawei Liang and Tesheng Hsiao. Admittance control of powered exoskeletons based on joint torque estimation. *IEEE Access*, 8:94404–94414, 2020.
- [77] Richard L. Lieber, Thomas J. Roberts, Silvia S. Blemker, Sabrina S. M. Lee, and Walter Herzog. Skeletal muscle mechanics, energetics and plasticity. *Journal of Neuroengineering and Rehabilitation*, 14:1–16, 2017.
- [78] Dylan P Losey, Craig G McDonald, Edoardo Battaglia, and Marcia K O’Malley. A review of intent detection, arbitration, and communication aspects of shared control for physical human–robot interaction. *Applied Mechanics Reviews*, 70(1), 2018.

- [79] Nathaniel S Makowski, Lisa M Lombardo, Kevin M Foglyano, Rudi Kobetic, Gilles Pinault, Stephen M Selkirk, and Ronald J Triolo. Walking after incomplete spinal cord injury with an implanted neuromuscular electrical stimulation system and a hinged knee replacement: a single-subject study. *Spinal Cord Series and Cases*, 6(1):1–8, 2020.
- [80] Hafiz Farhan Maqbool, Muhammad Afif Bin Husman, Mohammed I Awad, Alireza Abouhossein, Nadeem Iqbal, and Abbas A Dehghani-Sanij. A real-time gait event detection for lower limb prosthesis control and evaluation. *IEEE transactions on neural systems and rehabilitation engineering*, 25(9):1500–1509, 2016.
- [81] Benoit Mariani, Stephane Rochat, Christophe J Büla, and Kamiar Aminian. Heel and toe clearance estimation for gait analysis using wireless inertial sensors. *IEEE Transactions on Biomedical Engineering*, 59(11):3162–3168, 2012.
- [82] Giorgos Marinou, Lizeth Sloot, and Katja Mombaur. Towards efficient lower-limb exoskeleton evaluation: defining biomechanical metrics to quantify assisted gait familiarization. In *2022 9th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob)*, pages 1–8. IEEE, 2022.
- [83] Andres Martinez, Brian Lawson, Christina Durrough, and Michael Goldfarb. A velocity-field-based controller for assisting leg movement during walking with a bilateral hip and knee lower limb exoskeleton. *IEEE Transactions on Robotics*, 35:307–316, 2018.
- [84] Andres Martinez, Brian Lawson, and Michael Goldfarb. A controller for guiding leg movement during overground walking with a lower limb exoskeleton. *IEEE Transactions on Robotics*, 34(1):183–193, 2017.
- [85] Gilbert Masengo, Xiaodong Zhang, Runlin Dong, Ahmad B. Alhassan, Khaled Hamza, and Emmanuel Mudaheeranwa. Lower limb exoskeleton robot and its cooperative control: A review, trends, and challenges for future research. *Frontiers in Neurorobotics*, 16:1–25, 2023.
- [86] Christopher McCrum, Florence Lucieer, Raymond van de Berg, Paul Willems, Angélica Pérez Fornos, Nils Guinand, Kiros Karamanidis, Herman Kingma, and Kenneth Meijer. The walking speed-dependency of gait variability in bilateral vestibulopathy and its association with clinical tests of vestibular function. *Scientific reports*, 9(1):18392, 2019.

- [87] David P McMullen, Guy Hotson, Kapil D Katyal, Brock A Wester, Matthew S Fifer, Timothy G McGee, Andrew Harris, Matthew S Johannes, R Jacob Vogelstein, Alan D Ravitz, et al. Demonstration of a semi-autonomous hybrid brain-machine interface using human intracranial eeg, eye tracking, and computer vision to control a robotic upper limb prosthetic. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 22(4):784–796, 2013.
- [88] José Ramón Medina, Tamara Lorenz, and Sandra Hirche. Synthesizing anticipatory haptic assistance considering human behavior uncertainty. *IEEE Transactions on Robotics*, 31:180–190, 2015.
- [89] Martin Fodslette Møller. A scaled conjugate gradient algorithm for fast supervised learning. *Neural networks*, 6(4):525–533, 1993.
- [90] Christina Morawietz and Fiona Moffat. Effects of locomotor training after incomplete spinal cord injury: a systematic review. *Archives of physical medicine and rehabilitation*, 94(11):2297–2308, 2013.
- [91] Richard M Murray, Zexiang Li, S Shankar Sastry, and S Shankara Sastry. *A mathematical introduction to robotic manipulation*. CRC press, 1994.
- [92] Syam Prabhakaran Nair, Sheila Gibbs, Graham Arnold, Rami Abboud, and Weijie Wang. A method to calculate the centre of the ankle joint: A comparison with the vicon® plug-in-gait model. *Clinical Biomechanics*, 25(6):582–587, 2010.
- [93] Kumpati S Narendra and Anuradha M Annaswamy. Persistent excitation in adaptive systems. *International Journal of Control*, 45(1):127–160, 1987.
- [94] Rezvan Nasiri, Mohammad Shushtari, and Arash Arami. An adaptive assistance controller to optimize the exoskeleton contribution in rehabilitation. *Robotics*, 10(3):95, 2021.
- [95] Rezvan Nasiri, Mohammad Shushtari, Hossein Rouhani, and Arash Arami. Virtual energy regulator: A time-independent solution for control of lower limb exoskeletons. *IEEE Robotics and Automation Letters*, 6(4):7699–7705, 2021.
- [96] Vinh Q Nguyen, Russell T Johnson, Frank C Sup, and Brian R Umberger. Bilevel optimization for cost function determination in dynamic simulation of human gait. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(7):1426–1435, 2019.

- [97] Amin Nikoobin and Reza Haghghi. Lyapunov-based nonlinear disturbance observer for serial n-link robot manipulators. *Journal of Intelligent and Robotic Systems*, 55(2):135–153, 2009.
- [98] R. W. Nuckols, S. Lee, K. Swaminathan, D. Orzel, R. D. Howe, and C. J. Walsh. Individualization of exosuit assistance based on measured muscle dynamics during versatile walking. *Science robotics*, 6, 2021.
- [99] World Health Organization. Spinal cord injury. <https://www.who.int/news-room/fact-sheets/detail/spinal-cord-injury>, 2013.
- [100] Ciara M O’Connor, Susannah K Thorpe, Mark J O’Malley, and Christopher L Vaughan. Automatic detection of gait events using kinematic data. *Gait & posture*, 25(3):469–474, 2007.
- [101] Kara K Patterson, William H Gage, Dina Brooks, Sandra E Black, and William E McIlroy. Evaluation of gait symmetry after stroke: a comparison of current methods and recommendations for standardization. *Gait & posture*, 31(2):241–246, 2010.
- [102] Antonio Pedotti, V. V. Krishnan, and L. Stark. Optimization of muscle-force sequencing in human locomotion. *Mathematical Biosciences*, 38:57–76, 1978.
- [103] David Pinto-Fernandez, Torricelli Diego, Maria del Carmen Sanchez-Villamanan, Felix Aller, Katja Mombaur, Roberto Conti, Nicola Vitiello, Juan C. Moreno, and Jose Luis Pons. Performance evaluation of lower limb exoskeletons: A systematic review. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28:1573–1583, 2020.
- [104] Katherine L. Poggensee and Steven H. Collins. How adaptation, training, and customization contribute to benefits from exoskeleton assistance. *Science Robotics*, 6, 2021.
- [105] Nicola Postol, Steven Lamond, Margaret Galloway, Kerrin Palazzi, Andrew Bivard, Neil J. Spratt, and Jodie Marquez. The metabolic cost of exercising with a robotic exoskeleton: A comparison of healthy and neurologically impaired people. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28:3031–3039, 2020.
- [106] David Quintero, Dario J Villarreal, Daniel J Lambert, Susan Kapp, and Robert D Gregg. Continuous-phase control of a powered knee–ankle prosthesis: Amputee experiments across speeds and inclines. *IEEE Transactions on Robotics*, 34(3):686–701, 2018.

- [107] A Radmand, Erik Scheme, and K Englehart. A characterization of the effect of limb position on emg features to guide the development of effective prosthetic control schemes. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 662–667. IEEE, 2014.
- [108] Michael Raitor, Sandra Ruggles, Scott L Delp, C Karen Liu, and Steven H Collins. Lower-limb exoskeletons appeal to both clinicians and older adults, especially for fall prevention and joint pain reduction. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2024.
- [109] Christopher Richard, Mark R Cutkosky, and Karon MacLean. Friction identification for haptic display. *Proc. of Haptic Interfaces for Virtual Environments and Teleoperator Systems (HAPTICS)*, pages 14–19, 1999.
- [110] Robert Riener, Lars Lunenburger, Saso Jezernik, Martin Anderschitz, Gery Colombo, and Volker Dietz. Patient-cooperative strategies for robot-aided treadmill training: first experimental results. *IEEE transactions on neural systems and rehabilitation engineering*, 13(3):380–394, 2005.
- [111] Renaud Ronsse, Tommaso Lenzi, Nicola Vitiello, Bram Koopman, Edwin Van Asseldonk, Stefano Marco Maria De Rossi, Jesse Van Den Kieboom, Herman Van Der Kooij, Maria Chiara Carrozza, and Auke Jan Ijspeert. Oscillator-based assistance of cyclical movements: model-based and model-free approaches. *Medical & biological engineering & computing*, 49(10):1173–1185, 2011.
- [112] Giulio Rosati, James E Bobrow, and David J Reinkensmeyer. Compliant control of post-stroke rehabilitation robots: using movement-specific models to improve controller performance. In *ASME International Mechanical Engineering Congress and Exposition*, volume 48630, pages 167–174, 2008.
- [113] Mustafa Sarshar, Sasanka Polturi, and Lutz Schega. Gait phase estimation by using lstm in imu-based gait analysis—proof of concept. *Sensors*, 21(17):5749, 2021.
- [114] Hermann Schwameder, Markus Andress, Elisabeth Graf, and Gerda Strutzenberger. Validation of an imu-system (gait-up) to identify gait parameters in normal and induced limping walking conditions. In *ISBS-conference proceedings archive*, 2015.
- [115] Isabella Schwartz and Zeev Meiner. Robotic-assisted gait training in neurological patients: who may benefit? *Annals of biomedical engineering*, 43(5):1260–1269, 2015.

- [116] Keehong Seo, Young Jin Park, Jusuk Lee, Seungyong Hyung, Minhyung Lee, Jeonghun Kim, Hyundo Choi, and Youngbo Shim. Rnn-based on-line continuous gait phase estimation from shank-mounted imus to control ankle exoskeletons. In *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*, pages 809–815. IEEE, 2019.
- [117] Ajay Seth, Michael Sherman, Jeffrey A Reinbolt, and Scott L Delp. Opensim: a musculoskeletal modeling and simulation framework for in silico investigations and exchange. *Procedia Iutam*, 2:212–232, 2011.
- [118] Mojtaba Sharifi, Javad K Mehr, Vivian K Mushahwar, and Mahdi Tavakoli. Adaptive cpg-based gait planning with learning-based torque estimation and control for exoskeletons. *IEEE Robotics and Automation Letters*, 6(4):8261–8268, 2021.
- [119] Mojtaba Sharifi, Javad K Mehr, Vivian K Mushahwar, and Mahdi Tavakoli. Autonomous locomotion trajectory shaping and nonlinear control for lower limb exoskeletons. *IEEE/ASME Transactions on Mechatronics*, 27(2):645–655, 2022.
- [120] Bingquan Shen, Jinfu Li, Fengjun Bai, and Chee-Meng Chew. Motion intent recognition for control of a lower extremity assistive device (lead). In *2013 IEEE International Conference on Mechatronics and Automation*, pages 926–931. IEEE, 2013.
- [121] Erfan Shojaei Barjuei, Darwin G Caldwell, and Jesús Ortiz. Bond graph modeling and kalman filter observer design for an industrial back-support exoskeleton. *Designs*, 4(4):53, 2020.
- [122] M. Shushtari, H. Dinovitzer, J. Weng, and A. Arami. Ultra-robust estimation of gait phase. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30:2793–2801, 2022.
- [123] Mohammad Shushtari and Arash Arami. Human–exoskeleton interaction force estimation in indigo exoskeleton. *Robotics*, 12:66, 2023.
- [124] Mohammad Shushtari, Rezvan Nasiri, and Arash Arami. Online reference trajectory adaptation: A personalized control strategy for lower limb exoskeletons. *IEEE Robotics and Automation Letters*, 7:128–134, 2021.
- [125] Patrick Slade, Mykel J. Kochenderfer, Scott L. Delp, and Steven H. Collins. Personalizing exoskeleton assistance while walking in the real world. *Nature*, 610:277–282, 2022.

- [126] Mark Snaterse, Robert Ton, Arthur D Kuo, and J Maxwell Donelan. Distinct fast and slow processes contribute to the selection of preferred step frequency during human walking. *Journal of Applied Physiology*, 110(6):1682–1690, 2011.
- [127] Rong Song, Kai-yu Tong, Xiaoling Hu, and Le Li. Assistive control system using continuous myoelectric signal in robot-aided arm training for patients after stroke. *IEEE transactions on neural systems and rehabilitation engineering*, 16(4):371–379, 2008.
- [128] Mark W Spong. Modeling and control of elastic joint robots. 1987.
- [129] Mark W Spong, Seth Hutchinson, Mathukumalli Vidyasagar, et al. *Robot modeling and control*, volume 3. Wiley New York, 2006.
- [130] Tomomichi Sugihara, Yoshihiko Nakamura, and Hirochika Inoue. Real-time humanoid motion generation through zmp manipulation based on inverted pendulum control. In *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No. 02CH37292)*, volume 2, pages 1404–1409. IEEE, 2002.
- [131] Lei Sun, Honglei An, Hongxu Ma, and Jialong Gao. Real-time human intention recognition of multi-joints based on myo. *IEEE Access*, 8:4235–4243, 2019.
- [132] Katarzyna M Szostak, Laszlo Grand, and Timothy G Constandinou. Neural interfaces for intracortical recording: Requirements, fabrication methods, and characteristics. *Frontiers in Neuroscience*, 11:240291, 2017.
- [133] Lyndon Tang, Mohammad Shushtari, and Arash Arami. Imu-based real-time estimation of gait phase using multi-resolution neural networks. *Sensors*, 24(8):2390, 2024.
- [134] Candy Tefertiller, Kaitlin Hays, Janell Jones, Arun Jayaraman, Clare Hartigan, Tamara Bushnik, and Gail F Forrest. Initial outcomes from a multicenter study utilizing the indego powered exoskeleton in spinal cord injury. *Topics in spinal cord injury rehabilitation*, 24(1):78–85, 2018.
- [135] Nitish Thatte, Tanvi Shah, and Hartmut Geyer. Robust and adaptive lower limb prosthesis stance control via extended kalman filter-based gait phase estimation. *IEEE Robotics and Automation Letters*, 4(4):3129–3136, 2019.
- [136] Ekaterina B Titianova, Kauko Pitkänen, Ari Pääkkönen, Juhani Sivenius, and Ina M Tarkka. Gait characteristics and functional ambulation profile in patients with

- chronic unilateral stroke. *American Journal of Physical Medicine & Rehabilitation*, 82(10):778–786, 2003.
- [137] Heike Vallery, Edwin HF Van Asseldonk, Martin Buss, and Herman Van Der Kooij. Reference trajectory generation for rehabilitation robots: complementary limb motion estimation. *IEEE transactions on neural systems and rehabilitation engineering*, 17(1):23–30, 2008.
 - [138] Nicolas Van der Noot, Auke Jan Ijspeert, and Renaud Ronsse. Bio-inspired controller achieving forward speed modulation with a 3d bipedal walker. *The International Journal of Robotics Research*, 37(1):168–196, 2018.
 - [139] Tim J van der Zee, Emily M Munding, and Arthur D Kuo. A biomechanics dataset of healthy human walking at various speeds, step lengths and step widths. *Scientific data*, 9(1):704, 2022.
 - [140] Claude Vaney, Brigitte Gattlen, Véronique Lugon-Moulin, André Meichtry, Rita Hausammann, Denise Foinant, Anne-Marie Anchisi-Bellwald, Cécilia Palaci, and Roger Hilfiker. Robotic-assisted step training (lokomat) not superior to equal intensity of over-ground rehabilitation in patients with multiple sclerosis. *Neurorehabilitation and neural repair*, 26(3):212–221, 2012.
 - [141] Ivan Virgala and Michal Kelemen. Experimental friction identification of a dc motor. *International journal of mechanics and applications*, 3(1):26–30, 2013.
 - [142] Alexander Waibel, Toshiyuki Hanazawa, Geoffrey Hinton, Kiyohiro Shikano, and Kevin J Lang. Phoneme recognition using time-delay neural networks. *IEEE transactions on acoustics, speech, and signal processing*, 37(3):328–339, 1989.
 - [143] Eric R Westervelt, Jessy W Grizzle, Christine Chevallereau, Jun Ho Choi, and Benjamin Morris. *Feedback control of dynamic bipedal robot locomotion*. CRC press, 2018.
 - [144] David A Winter. *Biomechanics and motor control of human gait: normal, elderly and pathological*. 1991.
 - [145] David A Winter. Foot trajectory in human gait: a precise and multifactorial motor control task. *Physical therapy*, 72(1):45–53, 1992.
 - [146] David A Winter. Human balance and posture control during standing and walking. *Gait & posture*, 3(4):193–214, 1995.

- [147] K. A. Witte, P. Fiers, A. L. Sheets-Singer, and S. H. Collins. Improving the energy economy of human running with powered and unpowered ankle exoskeleton assistance. *Science Robotics*, 5, 2020.
- [148] Eric T Wolbrecht, Vicky Chan, David J Reinkensmeyer, and James E Bobrow. Optimizing compliant, model-based robotic assistance to promote neurorehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 16(3):286–297, 2008.
- [149] Herman J Woltring. A fortran package for generalized, cross-validatory spline smoothing and differentiation. *Advances in Engineering Software (1978)*, 8(2):104–113, 1986.
- [150] Amy R Wu, Florin Dzeladini, Tycho JH Brug, Federica Tamburella, Nevio L Tagliamonte, Edwin HF Van Asseldonk, Herman Van Der Kooij, and Auke J Ijspeert. An adaptive neuromuscular controller for assistive lower-limb exoskeletons: A preliminary study on subjects with spinal cord injury. *Frontiers in neurorobotics*, 11:30, 2017.
- [151] Xinyu Wu, Yue Ma, Xu Yong, Chao Wang, Yong He, and Nan Li. Locomotion mode identification and gait phase estimation for exoskeletons during continuous multilocomotion tasks. *IEEE Transactions on Cognitive and Developmental Systems*, 13(1):45–56, 2019.
- [152] Tingfang Yan, Andrea Parri, Virginia Ruiz Garate, Marco Cempini, Renaud Ronsse, and Nicola Vitiello. An oscillator-based smooth real-time estimate of gait phase for wearable robotics. *Autonomous Robots*, 41(3):759–774, 2017.
- [153] Yao Yan, Zhenlei Chen, Cheng Huang, Li Chen, and Qing Guo. Human-exoskeleton coupling dynamics in the swing of lower limb. *Applied Mathematical Modelling*, 104:439–454, 2022.
- [154] Fusheng Zha, Wentao Sheng, Wei Guo, Shiyin Qiu, Jing Deng, and Xin Wang. Dynamic parameter identification of a lower extremity exoskeleton using rls-pso. *Applied Sciences*, 9(2):324, 2019.
- [155] Jia-fan Zhang, Yi-ming Dong, Can-jun Yang, Yu Geng, Ying Chen, and Yin Yang. 5-link model based gait trajectory adaption control strategies of the gait rehabilitation exoskeleton for post-stroke patients. *Mechatronics*, 20(3):368–376, 2010.

- [156] Enhao Zheng, Silvia Manca, Tingfang Yan, Andrea Parri, Nicola Vitiello, and Qining Wang. Gait phase estimation based on noncontact capacitive sensing and adaptive oscillators. *IEEE Transactions on Biomedical Engineering*, 64(10):2419–2430, 2017.
- [157] Fangshi Zhu, Marcie Kern, Erin Fowkes, Taimoor Afzal, Jose-Luis Contreras-Vidal, Gerard E. Francisco, and Shuo-Hsiu Chang. Effects of an exoskeleton-assisted gait training on post-stroke lower-limb muscle coordination. *Journal of Neural Engineering*, 18:046039, 2021.