IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 6 February 2024, accepted 19 February 2024, date of publication 26 February 2024, date of current version 14 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3369680

RESEARCH ARTICLE

Learning User-Specific Control Policies for Lower-Limb Exoskeletons Using Gaussian Process Regression

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This work was supported in part by Mitacs, and in part by Human in Motion Robotics Inc.

ABSTRACT Robotic exoskeletons provide a viable means for enabling individuals with limited or no walking ability to traverse various surfaces with maximal external support to the patient's body. However, to achieve effective performance, it is crucial to consider anatomical differences in body size and shape among users. In this paper, we propose a framework to infer adapted user-specific policies using a small dataset from past experiments performed with twelve users wearing a lower-limb self-balancing exoskeleton. Our framework utilizes Gaussian Process Regression (GPR) to learn a mapping between user characteristics and control policy parameters. We also propose to use hindsight data relabeling to improve the performance of the controller. We experimentally test the output of the GPR model on new users and demonstrate its effectiveness in predicting user-specific walking parameters that lead to high performance. We also compare the performance of this control policy with an expert-tuned policy and show that our framework can reach comparable results without the need to perform expensive and unsafe tuning of the controller for new users.

INDEX TERMS Exoskeletons and prosthetics, machine learning for robot control, bipedal locomotion.

I. INTRODUCTION

Patients with neurological impairments often experience decreased movement and mobility, leading them to adopt a largely inactive lifestyle with extended periods of sitting [1]. Providing walking support for such patients is a fundamental component of their mobility that requires the lower limbs to be activated in order to step and support body mass [2]. Walking induces an increment in the physical workload, thus imposing a heightened demand on the cardiorespiratory system to provide adequate oxygen delivery to the working musculature [3]. Robotic exoskeletons provide a viable means for enabling individuals with limited or no walking ability to traverse the ground with maximal external support [4]. Extended sessions of walking with the assistance of a robotic exoskeleton hold promise for inducing moderate-intensity physical exercise, thus presenting a feasible means of augmenting cardiovascular fitness among individuals with spinal cord injury (SCI) [5].

Improving the robustness and stability (not falling down) of the lower-limb exoskeleton robot used for walking assistance is crucial to enhance patient safety. One way to achieve this is to provide the patient with crutches or other balance assistance devices to prevent the risk of falling during walking [6]. While some exoskeletons like ReWalk [7], Ekso [8], and Indego [9] rely on crutches for stability, there are only a few self-balancing exoskeletons available, such as the robot used in this study named XoMotion (Human in Motion Robotics Inc., Vancouver, Canada), as well as Atalante (Wandercraft, France) [10]. It is hence crucial to

The associate editor coordinating the review of this manuscript and approving it for publication was Pasquale De Meo.

FIGURE 1. Human subject wearing the XoMotion Beta 2 exoskeleton used in this work (Human in Motion Robotics Inc., Vancouver, BC).

devise safe frameworks for controlling these self-balancing robots, especially due to the essential need for interaction with the patient [11].

To ensure the performance of an exoskeleton walking controller for different individuals with diverse physical characteristics, it is important to adapt the policy parameters accordingly [12]. While trajectory optimization (TO) [13], [14] and model predictive control (MPC) [15], [16] have demonstrated promising results in generating stable gaits for bipedal robots, when it comes to the control of self-balancing exoskeletons, we require an automatic method to adjust the parameters of these controllers for new users with different weights and heights. One approach is to employ robust control approaches [17], [18] to find control policies that are robust to the variations, but in practice, this cannot yield desirable performance when the user characteristics change considerably.

To design a user-specific control policy for the lower-limb exoskeleton, it would be ideal to directly learn the key parameters of the individual's walking behavior during physical robot interactions. These essential parameters encompass various aspects, such as step length, step time, double and single support phases duration, MPC cost weights, swing foot trajectory, feet contact handling, stabilizer gains, and other relevant factors that contribute to the generation of walking patterns. By learning and adapting these crucial parameters through interaction with the physical robot, we can effectively tailor the control policy to suit each user's unique gait characteristics and ensure optimized performance. In a prior study [19], we developed a control strategy that can be applied to various users utilizing the exoskeleton, and it was achieved using a sample-efficient approach that required fewer than 30 iterations. However, this method would require conducting new experiments for each new user, which is not only expensive but also unsafe since the learning process involves inevitable failures that could potentially result in unsafe conditions. Ideally, we would like to use the data of the past experimental results for a set of users and infer the adapted user-dependent policy parameters. This way, we could bypass the procedure of tuning the controller for each new user.

As our problem is constrained by the number of users (and hence samples), deep learning [20] cannot be seen as a viable option, as a large number of samples is required for training the models. An alternative in such a case is Gaussian process regression (GPR) [21], [22]. GPR is a non-parametric Bayesian regression technique that models the target function as a Gaussian process (GP) [23]. One of the key advantages of GPR is its flexibility, as it can model any arbitrary function without imposing any assumptions on its form [24]. GPR is also able to handle noisy data, as it can capture the uncertainty associated with measurement errors, and has been successfully applied in various fields, such as robotics, finance, and environmental modeling [25]. GPR is selected for its ability to capture complex and non-linear mappings inherent in the relationship between user characteristics and control policy parameters. Unlike simpler regression methods, GPR offers a probabilistic framework that provides uncertainty estimates, crucial for safe and robust control. The choice was motivated by the intricate nature of the mapping, where user specifications involve multiple dimensions and intricate dependencies that GPR can model effectively [23], [26]. Various studies have leveraged the capabilities of GPR to enhance the performance and adaptability of assistive robots, showcasing its versatility in modeling complex relationships and improving control strategies [27], [28], [29].

In this paper, we propose to use GPR to learn a mapping between the user characteristics and parameters of the walking controller, using a small dataset extracted from a series of experiments performed with various (but a limited number of) users wearing a lower-limb self-balancing exoskeleton.

The main contributions of this work are as:

- We learn user-specific policy parameters for lower-limb self-balancing exoskeletons based on a small dataset of experiments performed with a few users. This offers a flexible and effective method for personalizing exoskeletons for individual users, without a need to perform new experiments for new users.
- We propose to use data relabeling in order to improve the performance of the controller in tracking desired commands. To the best of our knowledge, this is the first work that shows such an improvement.
- We present experimental validation of the framework on a new user. We also compare the performance of this controller with a tuned controller based on Bayesian Optimization (BO) [19] and show that our proposed approach in this work can achieve comparable performance without a need to perform new experiments.

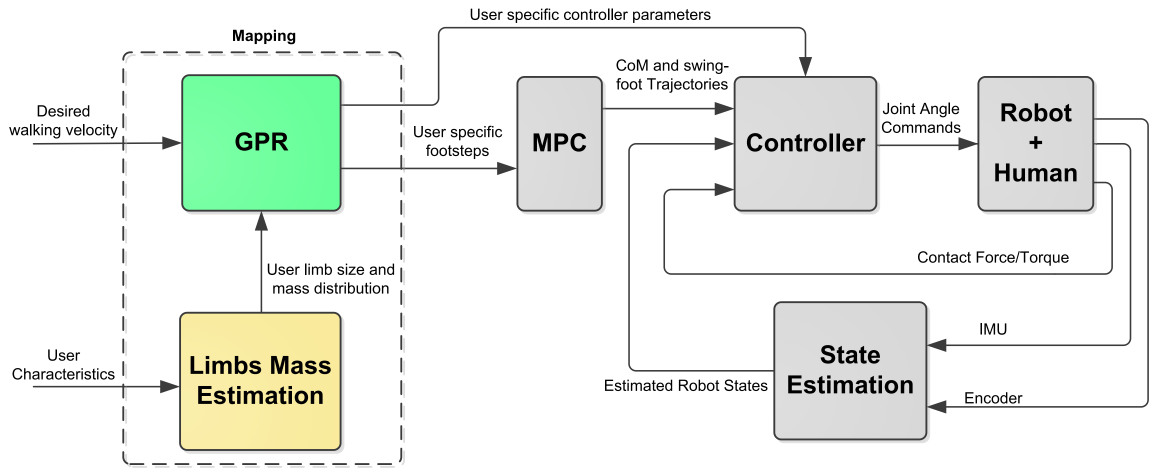

FIGURE 2. The block diagram of the control pipeline; the MPC block generates both the CoM and swing-foot trajectories based on the footstep locations derived from the GPR model. The controller block contains the inverse kinematics and stabilizer modules. The state estimator provides CoM and DCM estimations along with the base pose. The stabilizer module uses admittance control to track DCM trajectories via force measurement. The limbs mass estimator block utilizes the user's weight and height to estimate the distribution of mass across limbs, encompassing the torso, upper leg, and lower leg. Additionally, the mapping between the user characteristics and the user-specific parameters i.e. control policy parameters and the footsteps are also illustrated. The real system utilized in this research is comprised of the real robot and the human subject wearing it.

II. MATERIALS AND METHODS

A. STRUCTURE OF THE CONTROL PIPELINE

A block diagram of the control pipeline is shown in Fig. 2. We use a linear MPC to generate center of mass (CoM) and swing-foot trajectories given the footstep locations, similar to our previous work [19]. We assume piece-wise linear jerk of the CoM $\dddot{\boldsymbol{c}} = [\dddot{x}, \dddot{y}]^T$ over time intervals for the horizon NT, where N is the number of time steps into the future and T refers to the time step duration considered for discretization. The following optimization problem (which is transcribed to quadratic programming or QP) is solved at each control cycle to generate CoM trajectories consistent with the constraints on the Center of Pressure (CoP):

$$\min_{\dddot{\boldsymbol{c}}_i} \sum_{i=k}^{N+k-1} \alpha\|\dddot{\boldsymbol{c}}_i\| + \beta\|\dot{\boldsymbol{c}}_i - \dot{\boldsymbol{c}}_i^{ref}\|^2 + \gamma\|z_i - z_i^{ref}\|^2 \quad \text{(1a)}$$

$$\text{s.t.} \quad z_i \in \text{support polygon} \quad , \quad \forall i = 1, \ldots, N. \quad \text{(1b)}$$

$$\boldsymbol{\xi}_f = z_f = z_{ref}, \quad \text{(1c)}$$

in which z represents the CoP, and the superscript ref stands for the reference trajectories and α, β, and γ are positive scalars. The footsteps are pre-defined, and then the reference CoP trajectory z^{ref} is defined by connecting lines between either center of the footsteps, or the projection of the ankle joint on the ground. Moreover, $\boldsymbol{\xi} = [\xi_x, \xi_y]^T$ is the 2D divergent component of motion (DCM) ($\boldsymbol{\xi} = \boldsymbol{c} + \frac{\dot{\boldsymbol{c}}}{\omega}$), and Eq. (1c) makes sure that the robot is capturable (i.e., the robot can be stabilized without a need to take a step) at the end of the horizon [30].

The controller block diagram in Fig. 2 includes the inverse kinematics (IK) and the stabilizer module. Since our robot is position-controlled, we employ task-based IK using QP to trade off the tracking of the desired CoM and foot trajectories, while constraining the CoP to remain inside the support polygon of the feet [31].

First-order admittance control is applied to the ankle joints to regulate the responsiveness of the CoP modulation as [31]:

$$\begin{bmatrix} \dot{\theta}_r^c \\ \dot{\theta}_p^c \end{bmatrix} = A_{cop}(p^d \times f^m - \boldsymbol{\tau}^m) \quad (2)$$

$$A_{cop} = \begin{bmatrix} A_{cop,y} & 0 & 0 \\ 0 & A_{cop,x} & 0 \end{bmatrix} \quad (3)$$

where (θ_r^c, θ_p^c) are the commanded roll and pitch angles of the foot in contact with the ground surface, $p^d = [p_x^d \ p_y^d \ 0]$ indicates the desired CoP position and the measured contact wrench is denoted by $(f^m, \boldsymbol{\tau}^m)$. $A_{cop,x}$ and $A_{cop,y}$ stand for CoP admittance gains in the x and y directions, respectively. During the double-support phase, CoP must be transferred from one foot to the other. This is where foot force difference control (FFDC), originally introduced by Kajita et al. [32], comes into play. The concept of FFDC allows for precise control of the ground reaction forces acting on each foot, ensuring a smooth and stable transfer of the CoP. The control law incorporates both CoP position and vertical forces to regulate the foot force difference. Implementing FFDC involves using (v_{Lz}, v_{Rz}) to represent the velocities of the left and right foot in their sole frames as [31]:

$$v_{Lz}^c = v_{Lz}^d - 0.5\, A_{dfz}(\Delta f_z^d - \Delta f_z^m) + 0.5\, v_{vdc} \quad (4)$$

$$v_{Rz}^c = v_{Rz}^d + 0.5\, A_{dfz}(\Delta f_z^d - \Delta f_z^m) + 0.5\, v_{vdc} \quad (5)$$

where A_{dfz} is the FFDC admittance gain, $\Delta f_z = f_{Lz} - f_{Rz}$, and v_{vdc} denotes the velocity term added to compensate the vertical drift.

TABLE 1. Mapping between the user characteristics and the control policy parameters.

Inputs	Outputs
Height	CoP admittance gain in the x direction ($A_{cop,x}$)
	Foot force difference control admittance gain (A_{dfz})
Weight	Swing foot z-direction adjustment at the landing moment (adj_z)
	Step time (T_c)
	Step time ratio (ρ)

A kinematic-based approach is employed to estimate the base position and velocity for state estimation. We refer the readers to [19], [31], and [33] for more details.

B. LEARNING USER-SPECIFIC CONTROL PARAMETERS

For training the GPR, we have used data from the previous experiments where the controller is carefully tuned either by the expert or BO [19], [34]. To avoid repeating this procedure for every new user, here we use GPR to learn the mapping between user characteristics and controller parameters, using previous successful experimental data. The inputs used in the model are the user's weight and height of the CoM and the command walking velocity. The outputs of the model are five parameters that we have identified as having the maximum impact on the performance of our controller for different users. These parameters significantly influence the stability and shape of the motion, and their careful selection ensures effective and safe walking behavior tailored to individual users. These parameters are:

- The CoP admittance gain in the x direction ($A_{cop,x}$): This parameter affects the CoP response to the DCM tracking error and is introduced in Eq. (2) and (3). A higher value of $A_{cop,x}$ results in a faster pitch of the foot in response to sagittal CoP deviations. The use of $A_{cop,x}$ allows for greater adaptability and responsiveness of the exoskeleton to a variety of walking conditions, thereby improving the overall performance of the system.
- The foot force difference control admittance gain (A_{dfz}): This parameter controls the distribution of forces between the left and right foot of the exoskeleton during the double support phase as shown in Eq. (4) and (5).
- The swing foot trajectory adjustment in the z-direction at the foot landing moment (adj_z): This parameter adjusts the swing foot trajectory to ensure that the foot lands at the desired location at the end of the swing phase. This value needs to be adapted for each user, as the weight of the user affects the deformations in the robot structure.
- The step time (T_c): This parameter indicates the duration of taking one step, which is the sum of the duration of the double support phase and the single support phase. A longer step time means that the exoskeleton should take a longer step given a specific walking velocity.
- The step time ratio (ρ): This parameter indicates the relative duration of the double support phase and the step time T_c and is a critical parameter for maintaining a stable gait.

The mapping between the user characteristics and the control policy parameters are explained in Table 1 and is also shown in Fig. 2.

C. GAUSSIAN PROCESS REGRESSION

In Gaussian Process Regression (GPR), the target function $f(\mathbf{x})$ is modeled with a mean function $m(\mathbf{x})$ and covariance function $k(\mathbf{x}, \mathbf{x}')$. The mapping between input $\mathbf{x}$ and output $\mathbf{y}$ is learned using a small dataset $(X, \mathbf{y})$. GPR employs Bayes' rule to infer the posterior distribution over $f(\mathbf{x})$. The likelihood of data given f assumes Gaussian distribution with mean $f(\mathbf{x})$ and variance σ_n^2, representing noise. The prior distribution over f is determined by the choice of kernel function, capturing covariance between input points.

For our study, we selected the Radial Basis Function (RBF) and Dot Product kernels. The RBF kernel governs smoothness with a length scale parameter l, and the Dot Product kernel, representing linearity, includes a scale factor σ_0. The combined kernel is $k = c_1 k_{rbf} + c_2 k_{dot}^p$, where the constants c_1 and c_2, and the power p are set accordingly. This kernel choice is tailored for our problem, capturing both smooth and linear relationships in the data. The RBF kernel allows flexibility, while the Dot Product kernel efficiently models linear trends. Our approach leverages these kernels to enhance the adaptability and performance of the GPR model for user-specific control policies in lower-limb exoskeletons.

D. DATA RELABELING

Data relabeling is a technique used in machine learning to reassign labels to the training data to improve the performance of a learning model. It involves modifying the labels of the data instances in a dataset to better match the true label, or to match the output of a more accurate model. This technique can be particularly useful in robotics applications where the performance of the system is affected by the accuracy of the training data. Especially, when the desired behavior can be represented by a goal, it has been shown to improve policy learning in both reinforcement [35] and iterative supervised learning [36] settings.

In our study, the goal of the controller is to minimize the tracking error of the commanded walking velocity. In our experiments, we collected a dataset with different users and walking speeds, where each experiment corresponds to a certain set of walking parameters including the step length and step time. However, the Beta 2 exoskeleton did not accurately follow the desired walking velocity due to the deformations in its mechanical structure and other sources of imperfection. While we compensated for the vertical direction of the swing foot at the moment of landing (adj_z), there were still discrepancies in the sagittal direction compared to the nominal step length, resulting in smaller steps. To address this problem, we employed a data relabeling technique in which we estimated the distance between the feet at the moment of swing foot landing through a kinematic-based approach [37], estimating the realized step length. For

FIGURE 3. Snapshots of a test user walking with the XoMotion Beta 2 exoskeleton, using predicted walking parameters from GPR (the sequence is from left to right taking two steps).

this estimation, we used inertial measurement unit (IMU) sensors located at the robot's base (pelvis) and its feet, as well as the joint angles. A reasonable assumption was to consider that the deformations take place at the hip joints. Using this estimation, we relabeled the values corresponding to the step location and timing of the gait. We show in Section II-E3 that this relabeling procedure can improve performance in terms of velocity tracking.

E. EXPERIMENTAL SETUP AND PROTOCOL

The XoMotion Beta 2 exoskeleton can accommodate users of varying heights and weights with adjustable link sizes for thighs and shanks. Weighing approximately 74 kg, the robot has 6 degrees of freedom in each leg - 3 at the hip joint, 1 at the knee joint, and 2 at the ankle joint - providing a full range of motion. The robot is capable of traversing flat and sloped ground, ascending and descending stairs, and walking in different directions by turning and sidestepping while maintaining balance.

To collect data for training GPR, we performed a set of experiments where diverse individuals walked at different velocities. These experiments were approved by the Research Ethics Board of Simon Fraser University (#30001570). We employ conventional anthropometric measurement techniques to acquire diverse individuals' physical attributes, encompassing measurements of limb lengths. Furthermore, we assess the distribution of mass across various limbs, a critical factor for incorporation into model-based control methodologies [38], [39].

We used a similar approach to our previous work [19] that employed dummy weights with similar inertia distributions to a range of users, which allowed us to tune the controllers on the robot without any safety issue and generate data that closely resembles the behavior of actual human users. Also, the length of the robot's links is modified to account for users of varying heights and weights. The XoMotion Beta 2 exoskeleton is designed to accommodate users with heights ranging from 155 to 190 cm and weights between 50 and 100 kg. These ranges encompass around 99 percent of the population's height and approximately 80 percent of the population's weight, based on NHANES[1] data [40].

[1]National Health and Nutrition Examination Survey.

TABLE 2. Characteristics of the users whose data were used for training GPR.

Users	Total weight [kg]	CoM height [cm]
Robot + user-1	124	77.7
Robot + user-2	146.7	80.4
Robot + user-3	174	82.7
Robot + user-4	124	90.3
Robot + user-5	146.7	93.3
Robot + user-6	174	95.8
Robot + user-7	124	94.9
Robot + user-8	146.7	98.2
Robot + user-9	174	101
Robot + user-10	130	86
Robot + user-11	164.3	97.4
Robot + user-12	172.8	101

In Table 2, the total weight and the height of the center of mass are presented, representing the combined measurements of the robot and users wearing the exoskeleton. For each user, we performed walking in the forward direction at velocities ranging from 0.1 km/h to 1.0 km/h in increments of 0.1 km/h, resulting in ten distinct velocities per participant. In the following, we present our results in three different scenarios. In the first scenario, we evaluate the performance of the GPR model on a new user. In the second scenario, we compare the result of the GPR with a controller that is tuned by BO [19]. Finally, the third scenario demonstrates the effect of data relabeling on improving reference velocity tracking.

1) SCENARIO 1: TEST A NEW USER

In this scenario, we tested the predictions of the GPR model by implementing the learned control policy on a new user. The total weight of the robot and the new user for testing the method was 142 kg, and the corresponding CoM was 86.5 cm.

2) SCENARIO 2: COMPARISON WITH EXPERT TUNING

We conducted a comparative analysis between the GPR model and Bayesian Optimization (BO) in a specific scenario, evaluating their performance without specifying a particular walking velocity. In our previous work [19], BO was employed and regarded as an expert tuning method for reference in the comparison.

3) SCENARIO 3: DATA RELABELING RESULTS

In this scenario, we evaluate the effectiveness of the data relabeling process presented in Section II-D. To do that, we trained the GPR model with and without relabeling and then used it for two different walking velocities.

III. RESULTS AND DISCUSSIONS

As mentioned earlier, the first scenario assesses the efficacy of the GPR model through experiments conducted with a new user. These experiments encompass walking at various velocities within the range tested during the training phase, from 0.1 to 1.0 km/h. Notably, all experiments

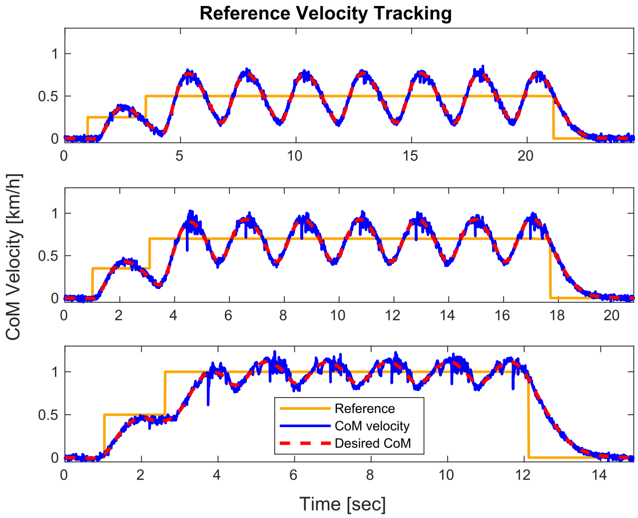

FIGURE 4. **The reference velocity tracking by the new user based on the prediction of the GPR model. The results are shown for the test user walking with 0.5, 0.7, and 1.0 km/h from top to bottom.**

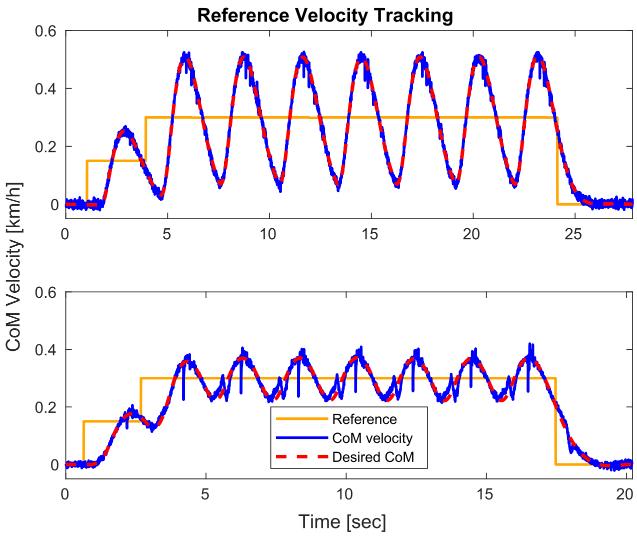

FIGURE 5. **Comparison of the prediction of the GPR model (top) and the results of the expert tuning (bottom) for reference velocity tracking. The results are shown for the test user walking at 0.3 km/h.**

utilizing the predicted GPR parameters exhibited stability, as demonstrated in Figure 3, which presents snapshot photos from one such experiment. Additionally, Figure 4 depicts the reference velocity tracking for the new user walking at 0.5, 0.7, and 1.0 km/h. The figure illustrates the robot's stable walking performance while accurately tracking different velocities.

The second experimental scenario involves a comparison between the GPR model's output and the results obtained through expert tuning. As shown in Fig. 5, the GPR prediction leads to larger CoM fluctuations in the sagittal direction, however, the average desired velocity is still tracked decently. The actual average velocity during the steady-state part of the motion is about 0.297 km/h for the expert tuning (BO) case and about 0.288 km/h for the GPR prediction. The main

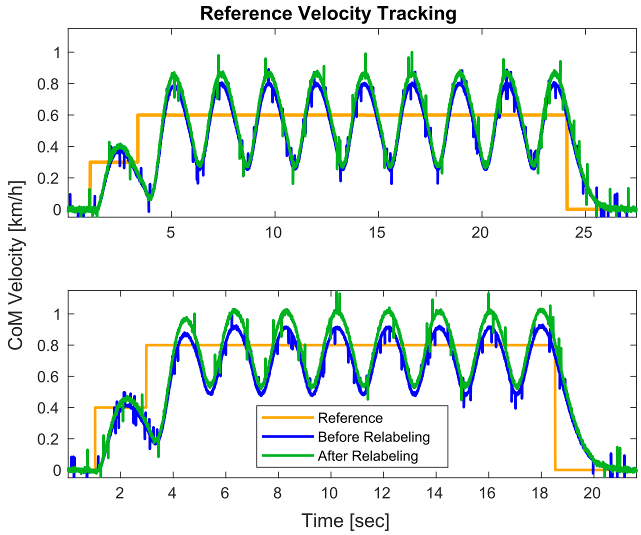

FIGURE 6. **The reference velocity tracking by the new user based on the prediction of the GPR model. The results are shown for the cases before and after relabeling for walking with 0.6 km/h (up) and 0.8 km/h (down).**

reason for much larger fluctuations for the GPR case is that it selected a larger single support phase period which results in walking which needs to be statically stable. Certainly, the GPR model's performance for a new user may not match the efficiency of expert tuning, especially for a small dataset. Nevertheless, the results indicate that we can still achieve a satisfactory outcome.

In the third scenario, we utilized the output of the data relabeling method to enhance the tracking of reference velocity. Figure 6 shows the reference velocity tracking, before and after relabeling the data, for walking with 0.6 km/h and 0.8 km/h. The results show that the actual average walking velocity was improved from around 0.55 to 0.6 km/h, and from around 0.72 to 0.8 km/h, for each of these cases perfectly matching the desired walking velocity.

IV. CONCLUSION AND FUTURE WORK

In this paper, we proposed a framework for automatically inferring the adapted gait parameters of an exoskeleton walking controller, using a small dataset of previous experiments for different users. As the real-world dataset is small and not highly diverse, we proposed to resort to using Gaussian Process Regression (GPR) which is known to be sample-efficient. We also proposed a relabeling procedure of the collected data to improve the performance of the learned model. After applying data relabeling, we observed a notable improvement of around 10% in the accuracy of reference velocity tracking. Through a set of experimental tests, we showed the merit of our framework in finding adapted control parameters for new users without a need to perform re-tuning of the controller for them. While the output of the GPR model exhibits some increase in overshoot during reference velocity tracking compared to expert tuning, it is important to note that the resulting motions remain remarkably robust and human-like. In the future, we plan to test our algorithm on a larger number of new users for further validation. Also, it would be interesting to extend the framework such that we continually improve the performance of the model as more and more data from new users becomes available. Finally, we are also interested in taking into account safety considerations when learning the parameters of the controller for new users in the presence of disturbances and model uncertainties.

ACKNOWLEDGMENT

The authors would like to thank the Human in Motion Robotics (HMR) Team for their support. The research was performed at Simon Fraser University, and experimental tests were conducted on a wearable robotic exoskeleton designed and manufactured by Human in Motion Robotics Inc.

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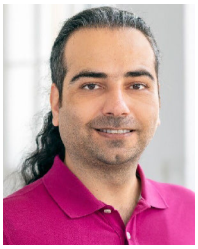

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