Combined Learning of Exoskeleton Mid-level Assistance Profiles and Low-level Control Parameters

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1 Motivation

Lower limb exoskeletons are wearable devices designed to assist human gait by supplying external torque at the knees, hips, or ankles. They show potential to reduce the metabolic burden of walking, enhance rehabilitation outcomes, and support healthy users in physically demanding tasks [1, 2]. A critical challenge, however, lies in adaptive and individualized control [3]. Users vary widely in physiological factors such as leg strength, stride kinematics, and preferred cadence, and exoskeletons deployed in the real world must respond to changing environments. While numerous studies used human-in-the-loop optimization to tailor the amplitude and timing of the reference trajecetory [4, 5], they typically fix the low-level controller parameters (e.g., PID parameters). This separation can limit the exoskeleton's capacity to improve energetic efficiency and satisfy essential safety and stability requirements – stability being vital for wearable devices that must guarantee safe user interaction. In this work, we employ Bayesian optimization for combined learning of the mid-level reference trajectory and the low-level PID parameters of a knee exoskeleton.

2 Methodology

This work addresses the combined learning of mid-level and low-level parameters, see Figure 1. We apply the SCONE simulation framework [6] for detailed biomechanics simulations. Specifically, we employ a reflex-based controller [7] for predictive gait simulations [8]. The biomechanical simulations utilize a planar detailed neuromuscular model, featuring 18 muscles and 9 degrees of freedom. The parameters of the exoskeleton controller are optimized through Bayesian optimization.

2.1 Assistance Profile Parameterization

The mid-level control parameters define the parametric reference trajectory for knee exoskeleton assistance, which is represented by a periodic cubic spline. This spline-based representation allows the exoskeleton to deliver torque in a smooth and adaptable manner throughout the gait cycle. The reference trajectory is parameterized by a set of control points $\mathbf{p} = \{p_1, p_2, \dots, p_N\}$, each corresponding to a specific time point in the gait cycle. The reference trajectory is then determined by adjusting the amplitude shifts θ_{amp} and the temporal shifts θ_{temp} of these control points. The set of amplitude shifts θ_{amp} modifies the amplitude of the reference trajectory at selected control points:

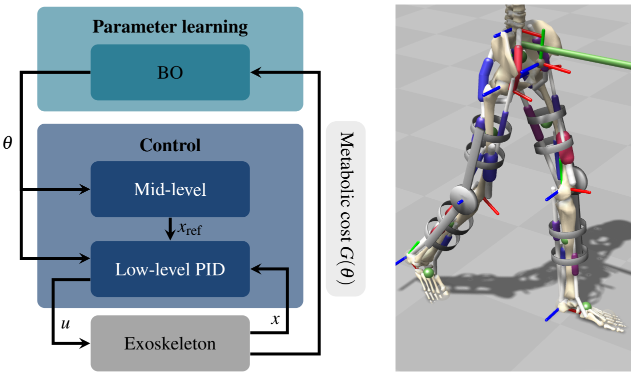

Figure 1: Illustration of the hierarchical human-in-the-loop learning and control framework for combined learning of mid- and low-level control parameters (left) and the SCONE [6] model used for simulation experiments (right).

$$\theta_{\text{amp}} = \{\Delta p_1, \Delta p_2, \dots, \Delta p_N\}, \quad \Delta p_i \in \mathbb{R}, \tag{1}$$

where Δp_i represents a relative change in amplitude of the reference trajectory at control point i. This enables the exoskeleton to adjust the level of assistance applied at different gait phases, adapting to variations in user effort and biomechanical needs. The set of temporal shifts θ_{temp} adjusts the timing of the reference trajectory by shifting the control points along the gait cycle:

$$\theta_{\text{temp}} = \{\Delta t_1, \Delta t_2, \dots, \Delta t_N\}, \quad \Delta t_i \in \mathbb{R}, \tag{2}$$

where Δt_i is the time shift (in milliseconds) for control point i. This allows the exoskeleton to synchronize assistance more precisely with the user's movement, improving efficiency and comfort. Given a set of adjusted control points $\mathbf{p}' = \mathbf{p} + \theta_{\text{amp}}$ at shifted time instants $t' = t + \theta_{\text{temp}}$, the periodic cubic spline $x_{\text{ref}}(t)$ defining the reference trajectory is constructed as $x_{\text{ref}}(t) = S(t'; \mathbf{p}')$, where $S(t'; \mathbf{p}')$ is the cubic spline interpolating the modified control points.

2.2 PID Controller Parameterization

The low-level control is handled by a PID controller, which regulates the torque applied by the exoskeleton actuators to track the desired reference trajectory. The set of PID parameters is defined as

$$\theta_{\text{PID}} = \bigcup_{i=1}^{n} \theta_{\text{PID}}^{i}, \; \theta_{\text{PID}}^{i} = \{K_P^i, K_I^i, K_D^i\}, \tag{3}$$

where $n \in \mathbb{N}$ is the number of joints, and K_P^i, K_I^i, and K_D^i denote the proportional, integral, and derivative gains of the i-th joint, respectively. Tuning these parameters is essential for achieving precise reference tracking, ensuring that the exoskeleton delivers assistance smoothly and in synchronization with the user's motion. Properly adjusted PID parameters improve control accuracy, minimize tracking error, and prevent excessive oscillations, contributing to closed-loop stability and safe user interactions. The parameters of each knee joint are learned independently. Note that we are not limited to PID parameter learning. In principle, parameters for any control concept can be learned, such as model predictive control.

2.3 Combined Parameter Learning

By combined optimization of θ_{PID} alongside the reference trajectory parameters θ_{amp} and θ_{temp}, the exoskeleton can dynamically adjust both the timing and magnitude of the reference trajectory while ensuring robust and stable torque application. The full parameter set is given by $\theta = \theta_{\text{PID}} \cup \theta_{\text{amp}} \cup \theta_{\text{temp}}$. The optimization problem is given by

$$\theta^* = \arg\min_{\theta \in \Theta} G_{\text{met}}(\theta) + G_{\text{stab}}(\theta), \tag{4}$$

where G_{met} quantifies the closed-loop metabolic cost [9] of the system under the parameter configuration θ and G_{stab} is a heuristic penalty added when the parameterization θ leads to unstable gait, i.e., the center of mass falls below a threshold of 0.3 m. A Bayesian Optimization loop [10] iteratively updates θ by simulating assisted gait in the SCONE software, evaluating metabolic cost, and refining a Gaussian process surrogate [11]. This process systematically explores the parameter space, balancing performance improvement and uncertainty reduction, to find an optimal configuration that minimizes metabolic cost while maintaining heuristically stable gait dynamics.

3 Results

Simulation results demonstrated that combined optimization of the reference trajectory and PID parameters for a knee exoskeleton led to notable improvements in both metabolic efficiency and stability. The best-performing controller configuration, which simultaneously optimized the PID parameters θ_{PID}, amplitude shifts θ_{amp}, and temporal shifts θ_{temp}, achieved a metabolic cost reduction of 8.92%, surpassing all other tested configurations, see Figure 2 and Table 1. The optimized reference trajectory does not currently incorporate physical constraints or enforce trackability. However, the combined optimization of reference trajectory parameters and PID parameters results in stable gait and a reduction in metabolic cost.

In contrast, optimizing only the reference trajectory (θ_{amp}) under fixed PID settings yielded a lower reduction of 5.3%, while incorporating PID parameter learning alongside amplitude shifts ($\theta_{\text{PID}}, \theta_{\text{amp}}$) led to a 6.58% reduction. Similarly, optimizing both amplitude and temporal shifts ($\theta_{\text{amp}}, \theta_{\text{temp}}$) without adjusting PID parameters resulted in a 6.49% reduction. The results are summarized in Table 1. These comparisons indicate that combined optimization of PID parameters and reference trajectory parameters provides the greatest metabolic benefit, as even small adjustments to θ_{PID} improved the dynamic application of assistance.

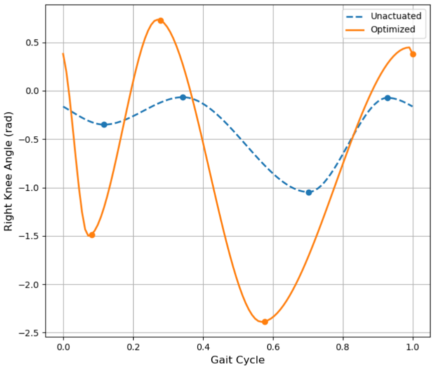

Figure 2: Combined learning of all parameters: Initial, unactuated knee angle (dashed blue), optimized knee angle reference (solid orange), and spline control points (dots).

While the optimization process was primarily designed to promote energy efficiency, stable gait was not always guaranteed. A rigorous measure of stability was not included in the objective function. Thus, certain parameter configurations at times led to undesired gait perturbations. Nevertheless, including θ_{PID} in the optimization did generally help reduce abrupt or mistimed assistance, illustrating the important role of low-level control learning. Our results highlight the potential of a combined optimization of mid- and low-level control parameters to improve metabolic cost while making strides toward robust and safe exoskeleton interaction.

4 Conclusions and Outlook

By combined learning of the mid-level reference trajectory and low-level PID parameters, this work contributes a more comprehensive framework for personalized exoskeleton control. Our results showed the highest reduction in metabolic cost when learning mid-level and low-level control parameters in a combined way. In the present work, gait stability was achieved heuristically by incorporating a penalty function that discourages unstable gait solutions. Looking forward, a key extension is to incorporate rigorous stability-informed learning into the Bayesian optimization loop, e.g., [12, 13], ensuring that parameters proposed by the optimizer lead to stable gait. This next step will enable control-theoretic safety guarantees during online learning. Furthermore, we plan to consider preference-based [14] and context-dependent learning of the controller parameters, depending on the situation the exoskeleton is used in. A multimodal foundational model might provide context information based on images taken and map or user input provided.

Table 1: Comparison of different controller parameterizations and the resulting metabolic cost reductions.

Optimized Parameters	Metab. Reduction (%)
θ_{amp}	5.3
$\theta_{\text{PID}}, \theta_{\text{amp}}$	6.58
$\theta_{\text{amp}}, \theta_{\text{temp}}$	6.49
$\theta_{\text{PID}}, \theta_{\text{amp}}, \theta_{\text{temp}}$	8.92

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