Enhancing Hip Exoskeleton Tuning Performance with Machine Learning: An Anthropometric Data-Driven Approach

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Abstract: Hip exoskeletons offer significant potential for enhancing human movement, especially for those with mobility impairments. However, optimizing their performance typically involves lengthy discrete and continuous optimization methods. To address this, we propose a novel approach using machine learning to predict controller parameter classes, aiming to improve the tuning process. Our method relies on subject-specific anthropometric data to predict optimal controller parameters for hip exoskeletons. Through a machine learning framework, we develop predictive models to determine the most effective parameter settings tailored to individual users. By employing feature engineering, data synthesis techniques, and model training, we enhance the initialization of Bayesian Human-in-the-loop (HIL) optimization. Results indicate that our machine learning models can predict control parameter classes with 75% accuracy, leading to a 9.98% improvement in optimized exoskeleton performance for users.

Keywords: Assistive and Rehabilitation Robotics, Optimal Control, Machine Learning in modeling, estimation, and control

1. INTRODUCTION

Assistive exoskeletons represent a promising avenue for enhancing human locomotion performance and addressing mobility impairments. However, despite over a century of development efforts, exoskeleton devices are still hindered by various challenges (Chen et al. 2020; Han et al. 2021; Collins, Wiggin, and Sawicki 2015). Approaches to exoskeleton design have often relied on intuition and specialized hardware, resulting in only modest improvements compared to simulated expectations (Zhang et al. 2017). Additionally, the diversity in physiological and neurological responses among individuals poses a significant challenge to the widespread efficacy of these devices (Quesada, Caputo, and Collins 2016; Ren et al. 2019).

To address these challenges, recent research has focused on methods for automatically discovering and customizing assistance strategies, aiming to optimize device control systematically during use. One such approach, termed human-in-the-loop optimization (HIL), involves iteratively adjusting exoskeleton assistance patterns to minimize physiological costs (Zhang et al. 2017; Kim et al. 2017). This iterative process allows for real-time adaptation of assistance parameters based on user feedback, thereby potentially overcoming the limitations of traditional, fixed-parameter approaches (Han et al. 2021). However, most approaches still involve lengthy evaluation periods required by the current physiological metric: metabolic cost (Makin, Vignemont, and Faisal 2017). Data measurements for metabolic cost often adapt slowly (Handford and Srinivasan 2016), estimations require substantial historical data (Selinger et al. 2015), and signal readings are influenced by complex neurocognitive factors (Makin, Vignemont, and Faisal 2017).

Efforts to shorten protocol duration while maintaining optimization efficacy have prompted exploration into two main routes: metabolic cost estimation strategies (Gordon et al. 2022) or alternative objective functions (Zhang et al. 2017; Molinaro, Kang, and Young 2024; Ingraham et al. 2023). Moreover, advanced optimization techniques like Bayesian optimization hold promise in swiftly identifying optimal control parameters in a sample-efficient manner (Kim et al. 2017). Despite notable accomplishments in the realm of HIL optimization utilizing a combination of these strategies, enhancing its application further can lead to the development of better-performing controllers and greater scalability to diverse user populations.

The key to improving HIL may lie in harnessing a data-driven approach with machine learning techniques such as reinforcement learning, deep neural networks, and meta-learning (Fuentes-Alvarez et al. 2022; Li et al. 2022; Tu et al. 2021; Zheng et al. 2023). These approaches leverage extensive kinematic, force, or physiological datasets to gain insights into enhancing control (Diaz et al. 2022). One underutilized data source is anthropometric information. Body measurements can provide valuable insights into optimization techniques, yet such data is often scarce. Exoskeleton experiments typically involve fewer than 13 subjects (Diaz et al. 2022), resulting in limited observations per subject that hinder the utilization of comprehensive learning techniques.

Data synthesis is one way of mitigating data scarcity when collecting more data is infeasible or expensive (Figueira and Vaz 2022). This approach allows for the expansion of datasets while preserving the inherent trends and patterns of the original data. Enhancing these datasets can enable us to utilize them in improving current HIL techniques without the need for expensive additional data collection.

The focus of this work is to develop a comprehensive machine-learning pipeline that utilizes data synthesis techniques to enhance small anthropometric datasets to produce classification predictions for control parameters. We hypothesize that utilizing these predictions to initialize Bayesian search space will lead to an improved HIL optimization process. The novelty of this work lies in three aspects: 1) Enhancing small anthropometric datasets to be effectively utilized in machine learning models with high cross-validation scores, 2) Harnessing anthropometric data to make controller predictions, and 3) Improving the efficacy of an Electromyography (EMG)-based HIL optimization to tune controllers for leg swinging.

2. METHODS

2.1 Previous Experimental Data

In prior research (Echeveste and Bhounsule 2024), an experiment was conducted to optimize controller parameters for a hip exoskeleton designed to assist stationary leg swinging (Fig. 1). The device consisted of a custom-built hip exoskeleton device with a centric BLDC motor, with control managed by a Raspberry Pi 4 running Python (Fig. 2).

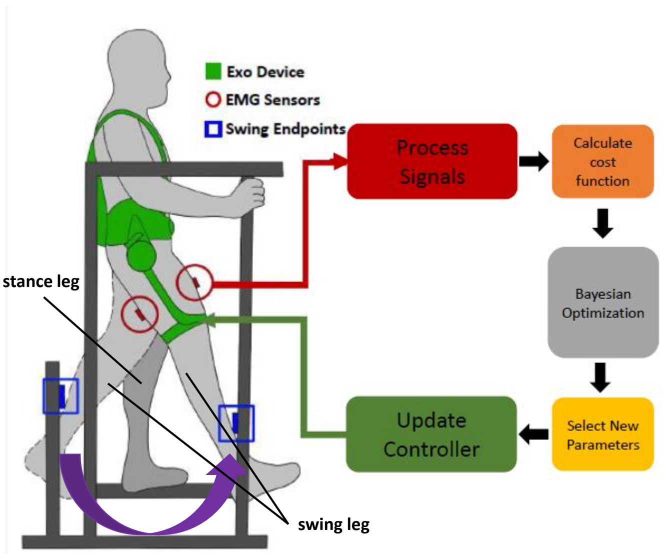

Fig. 1. Overview of EMG-HIL Bayesian Optimization established in precursor work

The control strategy was defined by four parameters that determined peak torques and angular positions throughout the swing to shape the torque profile for assisting leg swinging (Fig. 2). These parameters were optimized using Bayesian optimization, with electromyography (EMG) signals serving as the cost function. The optimization process involved constructing a probabilistic model of the objective function using a Gaussian Process (GP) and employing an acquisition function based on Expected Improvement (EI) to iteratively select parameter settings for evaluation. The cost function used in the optimization process, h^d, was defined as follows:

$$h^d = \sum_{n=1}^{4} \mathrm{rms}(M_n^d) \tag{1}$$

where M_n^d represents the EMG signals from different muscles during the swing phases. This cost function aggregates the root mean square (RMS) values of these signals to quantitatively evaluate the efficiency of the leg-swinging assistance.

The experimental protocol involved eight healthy participants (mean age: 26.3 years [$\sigma = 3.2$]; mean weight: 64.6 kg [$\sigma = 3.47$]; mean height: 165.33 cm [$\sigma = 11.13$]; male: 5, female: 3). The protocol consisted of acclimation, parameter optimization, and validation phases. EMG data from sensors placed on the rectus femoris and biceps femoris muscles were processed to compute cost functions individually for both forward and backward swinging phases using Eq. 1.

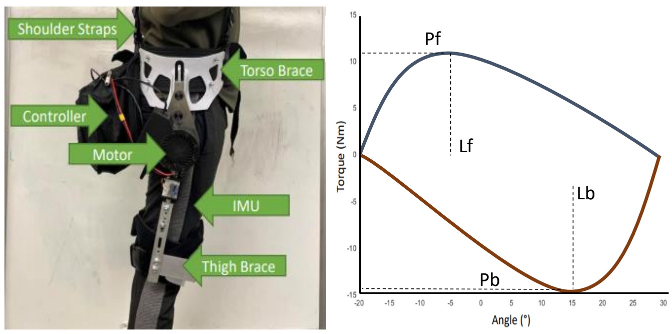

Fig. 2. Left) An illustration of the exoskeleton device used, highlighting important features. Right) An illustration of the relationship between torque and angle.

During the tuning phase, the Bayesian optimization algorithm iteratively identified optimal parameter sets for slow and fast swing frequencies. The goal was to converge on parameter sets that minimized cost functions derived from EMG signals, indicating efficient leg-swinging assistance. In the validation phase, the performance of the optimized parameters was compared against baseline conditions, including no device, zero torque, and generic control settings. Statistical analysis, including non-parametric tests, was conducted to assess differences between conditions. Additionally, subjective ratings of perceived effort using Borg's scale were collected to correlate with physiological responses.

The optimization process ensured data convergence and maximized the signal-to-noise ratio of EMG signals through rigorous data processing and analysis. The collected data aimed to explore whether control parameters could be predicted from subjects' anthropometric data to enhance device tuning for future users. Six anthropometric markers were sampled from each participant: height, weight, body fat percentage, leg girth, leg weight, and leg length. These measurements were combined to derive six new meaningful measurements: body mass index (BMI), lean mass, estimated leg strength, estimated leg volume, lean mass index (LMI), and lean leg density. These predictive features are detailed in Table 1. The outputs of interest were the eight parameters (four per controller, two controllers) targeting the two tuned swing frequencies.

Table 1. Predictive Features

Predictor	Symbol/Equation	Units
Height	h	cm
Weight	w	kg
Body fat	b	%
Leg circumference	Lc	cm
Leg weight	Lw	kg
Leg length	Ln	cm
BMI	$\frac{w}{h^2}$	$\frac{kg}{m^2}$
Lean Mass	$w(1-b)$	kg
Leg Strength	$\frac{Lw}{Ln}$	$\frac{kg}{m}$
Leg Volume	$4\pi LnLc^2$	m^3
LMI	$\frac{w(1-b)}{h}^2$	$\frac{kg}{m^2}$
Lean Leg Density	$\frac{Lw(1-b)}{LegVolume}$	$\frac{kg}{m^3}$

2.2 Data Processing

The anthropometric data undergo a multi-step process to synthesize a comprehensive dataset suitable for classification and prediction. The primary objective of the data processing pipeline is to effectively utilize the 12 predictive features to predict each of the eight possible outputs individually. The data processing steps include normalization, regularization, principal component analysis, outlier mitigation, data synthesis, and modeling (Fig. 3).

Normalization Normalization is employed to avoid magnitude bias and ensure generalizability across different data ranges. We integrated population data from online repositories (McConville 1980) with our sampled data to establish a comprehensive range of values. A Gaussian Mixture Model (GMM) was used to capture the mean and standard deviation of each anthropometric measurement from both data sources. This approach modeled complex, multimodal distributions, accurately reflecting the variability within the combined dataset. To integrate the data sources, we generated 1000 random samples from the GMM for each anthropometric predictor. These samples created robust distributions that informed our normalization process. The minimum and maximum values derived from these distributions ensured accurate and reliable normalization. By incorporating diverse population data and employing GMM, we minimized extrapolation errors and ensured that the normalized data accurately reflected true anthropometric variability.

Regularization Post-normalization, the data undergo regularization tailored for each output parameter. Regularization, particularly important in highly correlated datasets prone to multicollinearity, stabilizes parameter estimation and reduces model variance. We utilized the elastic net method, which combines Lasso (L1) and Ridge (L2) regularization. Elastic net strikes a balance between sparsity and coefficient shrinkage, controlled by an alpha parameter. In our experiments, we varied alpha to explore different levels of sparsity and shrinkage, ultimately selecting a balanced value of 0.5. The top four predictors, identified based on their coefficients' average magnitude across varying alphas, were selected for further analysis.

Principal Component Analysis (PCA) To reduce data dimensionality while preserving essential information, we applied Principal Component Analysis (PCA). PCA transforms the dataset into orthogonal variables called principal components, which capture the variance in the data. We focused on the first two principal components, which collectively explained a significant portion of the variance. This reduction in dimensionality facilitated more efficient subsequent analysis while retaining critical information.

Outlier Mitigation Outliers in the dataset were identified and mitigated using a robust linear model. By examining the major trend between the principal components and the output values, we detected deviations indicative of outliers. A threshold approach, analyzing residuals exceeding 3 standard deviations from the median, was employed to identify these anomalies. Outliers were then replaced with predicted model values, preserving dataset integrity and ensuring accurate statistical analysis and modeling.

Data Synthesis Synthetic data points were generated to augment the dataset while preserving the intrinsic characteristics of the original data. This augmentation was achieved using a modified Akima cubic Hermite interpolation method (Akima 1970). Akima interpolation was chosen for its ability to prevent overshoot, thus producing smooth and realistic synthetic data points that integrate well with the original dataset.

Synthetic data points were generated at a ratio of 1:4 relative to the real data. This ratio was selected to balance the influence of the original dataset with the additional synthetic data points, ensuring that the original data's statistical properties were preserved. Excessive synthetic data may overshadow the original data's variability, leading to potential overfitting.

Once the datasets for each output were enlarged, they were encoded to allow integration into a single representative dataset. Each output's corresponding enlarged dataset was assigned a dummy variable encoding information about which output it belonged to. The encoding values used to distinguish the outputs corresponded to parameters such as peak torque value (P), location value of the peak torque (L), forward aspect of the controller (f), backward aspect of the controller (b), fast swing frequency controller (F), and slow swing frequency controller (S). These binary variables served as indicators for the model to determine the output class for a subject given the experimental variables.

The synthetic data alone cannot generate new predictions without a model to interpret and learn from the data. Therefore, we first use the enriched dataset to train a machine learning model, which can then make predictions based on new subject data. We employ a meta-model to accomplish this. Base models, including a Gaussian

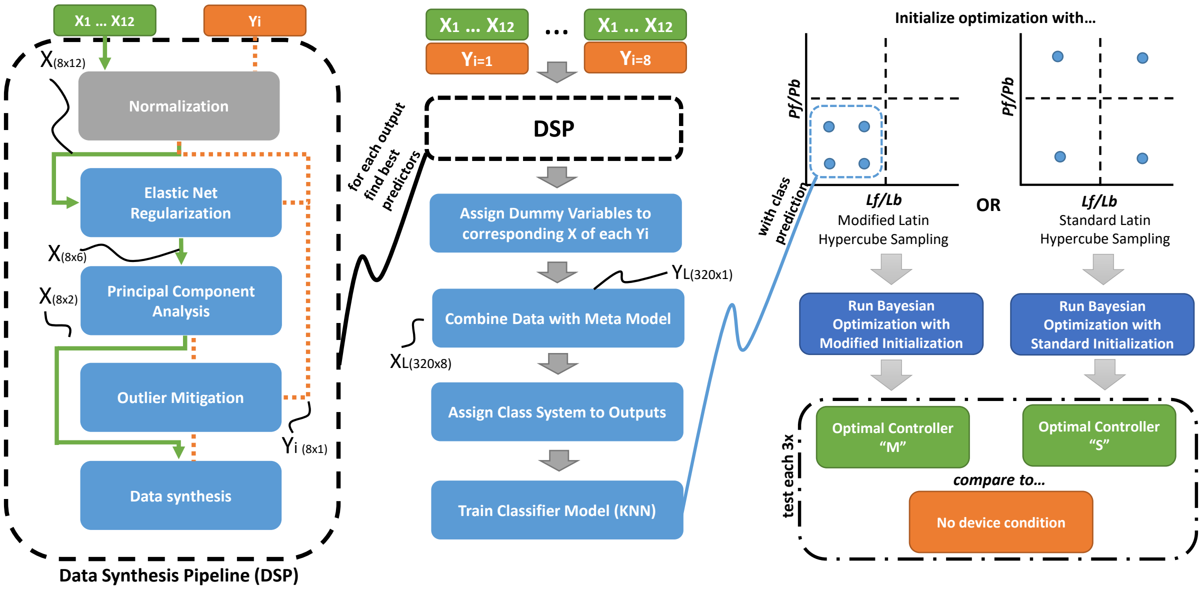

Fig. 3. An overview of the machine learning pipeline and how it is used to influence the initialization of Bayesian HIL optimization. Matrix dimensions are given in parenthesis and Pf/Pb/Lf/Lb refer to control parameters.

process (GP), support vector machine (SVM), and random forest, are utilized within the meta-model. The model's performance is assessed using cross-validation to ensure its generalizability.

The synthesized data enhances the training process by providing the model with a more diverse set of examples. By training the model on this enriched dataset, we improve its ability to generalize to new subjects, ultimately enhancing the performance of the human-in-the-loop optimization process. These predictions are then used to initialize the Bayesian optimization process within a targeted region of the parameter space, ensuring a more informed and focused search space.

2.3 Classification Model

From the synthesized data model, 320 data points are generated for use in ML classification techniques. Each output value is categorized into a class based on whether it falls above (high class) or below (low class) the midpoint value. The dataset is split, with 70% utilized as training data and the remaining 30% reserved for algorithm validation (testing data). We employ simple but powerful classification models—Logistic Regression, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)—to capture the complex patterns of the data. Before applying these models, we meticulously fine-tune their hyperparameters using the grid search cross-validation technique, specifically employing k-fold cross-validation (CV) with k set to 5. This approach not only optimizes the models' performance by refining hyperparameters but also assesses their ability to generalize to new data.

2.4 New Subject Data

Once the classification model is tuned and trained, we supply data from new subjects to make predictions on their output classes. This is done by taking the original six measurements from each subject, even if some measurements fall outside the bounds of the training data. We then process this data through similar aspects of the pipeline as the training data to ensure it is in the same format. These aspects include normalization, regularization, and PCA.

Once we have the input data in the desired format, we proceed to make classification predictions for either a slow controller or a fast controller. Each subject receives predictions about one swing frequency, and a controller for that swing frequency is tuned using HIL testing.

2.5 Experimental Procedure

Utilizing classification predictions from the machine learning algorithm, we enhance the initialization process for Bayesian optimization within a specific region of the parameter space. Focusing on a quadrant, we select four initial parameter sets using Latin hypercube sampling to narrow down the search space for potential high performance.

Compared to randomly selecting initial parameters from the entire parameter space, our approach allows for a more targeted exploration of promising configurations within the designated quadrant. Each parameter set defines the controller with two peak torque values and two peak location values for two separate swing directions.

To assess effectiveness, we conduct optimization experiments for both methods—assisted by classification predictions and without assistance—across multiple iterations. Parameters are iteratively selected until convergence or reaching the maximum number of trials.

Following optimization, we validate the optimal parameters obtained from each method against a no-exoskeleton condition, calculating a performance metric using the equation $\%\Delta = \left(\frac{\mu_{optimal} - \mu_{baseline}}{\mu_{baseline}}\right)$. Conditions are tested randomly to prevent bias, enabling an unbiased comparison across all experimental settings. This approach eval-

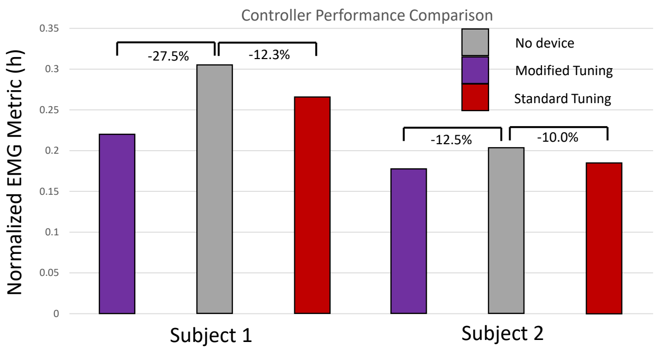

Fig. 4. Performance comparison between the two controllers tuned with and without the developed method against a baseline of no device.

uates the performance and robustness of our proposed initialization method in enhancing the efficiency and effectiveness of exoskeleton controller optimization.

3. RESULTS

The data synthesis meta-model demonstrates strong performance on the test dataset, achieving a coefficient of determination (R^2) of 0.7853 and a mean squared error (MSE) of 0.004. These metrics indicate the model's robustness in accurately synthesizing new data points that align well with the underlying patterns in the original dataset.

The classification model exhibits a high accuracy of 75% in predicting controller classes, correctly identifying 3 out of 4 classes for each subject (Table 2). This high accuracy demonstrates the model's effectiveness in categorizing controllers based on their performance characteristics and its reliability in discerning subtle differences in controller behavior.

Table 2. Class Predictions vs Actual

S1 Predicted:	1	2	2	1
S1 Actual:	1	2	2	2
S2 Predicted:	1	1	1	1
S2 Actual:	1	1	2	1

Comparing the optimization results obtained with and without prediction assistance, we found that the prediction-assisted optimization produces controllers that outperform those found without prediction assistance. For subject one, the optimization without prediction assist yields a percent reduction of 12.3% (p = 0.0023), while the prediction-assisted optimization achieves a greater reduction of 27.5% (p = 0.0008), indicating substantial improvement. Similarly, subject two experiences a benefit from the prediction-assisted optimization, with a percent reduction of 12.5% (p = 0.0001) compared to 10.0% (p = 0.0022) with no prediction assist, underscoring the consistent advantage of prediction assistance across different subjects.

These results highlight the effectiveness of utilizing prediction assistance in the optimization process, leading to significant improvements in controller performance for both subjects. This underscores the potential of leveraging machine learning techniques to enhance the efficiency and effectiveness of exoskeleton controller optimization.

4. DISCUSSION

This study introduces a novel approach to enhance the tuning process of hip exoskeletons by leveraging machine learning techniques to predict controller parameter classes based on subject-specific anthropometric data. Our results demonstrate the efficacy of this approach in improving the efficiency and effectiveness of exoskeleton customization.

One of the key outcomes of our study is the accuracy achieved by the classification model in predicting controller classes. This level of accuracy is a strong indication that anthropometric data significantly enhances the tuning process, for several reasons:

- **Baseline Comparison**: Without the incorporation of anthropometric data, baseline predictions typically achieve around 50% accuracy due to the binary nature of the classification task. Thus, achieving 75% accuracy represents a substantial improvement.
- **Complexity of the Task**: Predicting optimal control parameters for exoskeletons is inherently complex due to high variability in human physiology and biomechanics. The achieved accuracy demonstrates the model's ability to capture and leverage underlying patterns in the anthropometric data.
- **Limited Data**: Despite the small dataset size, this level of accuracy indicates strong model performance. This suggests that the data synthesis and processing steps effectively enhanced the dataset, allowing the model to generalize well.
- **Practical Impact**: This accuracy means that three out of four predictions are correct, leading to more efficient Bayesian optimization. This reduces the time and effort required to find optimal control parameters and enhances the user experience with the exoskeleton.

By harnessing subject-specific anthropometric data and employing classification models, we refine the sampling space of exoskeleton control parameters. This data-driven approach streamlines the optimization process, improving precision and customization of exoskeleton assistance strategies. These findings underscore the importance of leveraging data-driven techniques to enhance the efficiency of exoskeleton customization and optimization. Additionally, our study highlights the potential of small-dataset machine-learning techniques to enhance the performance and robustness of exoskeleton controllers.

Some limitations of our approach include the limited number of subjects and the number of classes that can be predicted. Currently, our pipeline predicts whether a parameter might be above average or below average. While this demonstrates an improved initialization for optimization, it does not possess the ability to predict control directly. In addition, a binary classification tends to lose important information and nuances of the control.

5. CONCLUSION

In conclusion, integrating machine learning with exoskeleton optimization holds promise for enhancing assistive robotics technology. This integration could transform the lives of individuals with mobility impairments.

Future research will delve into advanced machine learning algorithms like deep learning and reinforcement learning to boost prediction accuracy. In addition, these methods will accommodate finer grain classification to improve the accuracy. Incorporating real-time feedback mechanisms could enhance adaptability and responsiveness. Exploring the generalizability of this approach to other exoskeletons and assistive devices could broaden its impact.

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