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Continuous locomotion mode classification using a robotic hip exoskeleton

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***Abstract*— Human augmentation through robotic exoskeleton technology can enhance the user's mobility for a wide range of ambulation tasks. This is done by providing assistance that is in line with the user's movement during different locomotion modes (e.g., ramps and stairs). Several machine learning techniques have been applied to classify such tasks on lower limb prostheses, but these strategies have not been applied extensively to exoskeleton systems which often rely on similar control inputs. Additionally, conventional methods often identify modes at a discrete time during the gait cycle which can delay the corresponding assistance to the user and potentially reduce overall exoskeleton benefit. We developed a gait phase-based Bayesian classifier that can classify five ambulation modes continuously throughout the gait cycle using only mechanical sensors on the device. From our five able-bodied subject experiment with a robotic hip exoskeleton, we found that implementing multiple models within the gait cycle can reduce the classification error rate by 35% compared to using a single model ($p < 0.05$). Furthermore, we found that utilizing bilateral sensor information can reduce the error by 43% compared to using a unilateral information ($p < 0.05$). Our study findings provide valuable information for future exoskeleton developers to utilize different on-board mechanical sensors to enhance mode classification for a faster update rate in the controller and provide more natural and seamless exoskeleton assistance between locomotion modes.**

***Index Terms*— Exoskeleton, Machine Learning, Locomotion Mode, Continuous Classification, Sensor Fusion**

I. INTRODUCTION

Exoskeleton technology has drawn great attention for its potential benefit in multiple domains [1]. Specifically, lower-limb exoskeletons provide assistance at the joint during locomotion to augment the user for improved mobility. Accurately understanding the user's intent during locomotion is critical for controlling such devices. Different literature studies have indicated that an optimal assistance profile for these exoskeletons may vary depending on the user's locomotion mode (e.g., walking level ground vs. climbing stairs) [2–4]. In order to maintain maximum human exoskeleton performance, an accurate classification of the user's locomotion mode is beneficial. Different analytical methods have been implemented in the literature to classify locomotion modes such as deriving a slope angle from an inertial measurement unit [5]. However, these approaches do not yield robust results in real-time implementation due to inaccurate estimation (e.g., sensor noise and drift). One possible solution is to incorporate a machine learning-based (ML) classification strategy for its robustness in handling measurement noise and real-time implementation capability [6,7].

Several research groups in the wearable robotics field have investigated different ML techniques to classify the user's locomotion mode [7–9]. Simon *et al*. implemented a mode-specific classifier using a delayed mode transition decision for a robotic prosthesis achieving a classification error less than 0.5% [10]. However, the study was limited that the classifier was optimized specifically for a prosthesis application. For example, the study combined the ramp ascent and level ground modes as similar control parameters are required between these two modes for a robotic prosthesis control. However, this approach may not be a viable solution for robotic hip exoskeletons considering the difference in the hip kinetics between two modes. Long *et al*. utilized an SVM-based mode classifier for a full lower-limb exoskeleton achieving an error of 4% [11]. However, the study had a limitation in causing a large delay (transition prediction period being delayed up to a full step) in correctly classifying the transition period. Jang *et al*. applied a fuzzy inference system using the joint angle to classify the mode for a robotic hip exoskeleton achieving a classification error of 3% [12]. However, the study was limited as the model was only trained to classify stair and level ground modes and was not robust to different walking speeds.

Another limitation in the current literature is that these modes are classified in discrete times within the gait cycle. Classification at discrete times during the gait cycle is done to extract sensor information from a deterministic joint configuration where the data is most reliable (e.g., heel contact or toe off during the gait cycle). However, this could potentially result in providing a delayed and inaccurate assistance during the mode transition period. Ideally, transitioning between locomotion modes should be automatic, seamless, and natural to the user's movement. Huang *et al*. mitigated this problem, where multiple gait phase-dependent classifiers were designed for a continuous mode classification for a robotic prosthesis [6]. A similar strategy can be implemented in the exoskeleton application and potentially improve the performance in continuous classification. This prompted our study to leverage similar methods of mode classification using a robotic hip exoskeleton.

A more robust continuous mode classification will require

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an update rate equivalent to at least a pseudo real-time level (e.g., 50 Hz or more). To achieve this, we can utilize the user's gait phase information by segmenting the gait cycle into multiple phases and generating an ML model that can maximize the classification accuracy at a given window of gait phase [13]. While increasing the number of models within the gait cycle can improve the overall model performance, it may reduce feasibility due to limitations in real-time implementation (e.g., on-board microprocessor's memory capacity and the resolution of the gait phase estimator). Therefore, an optimal number of ML models that can achieve both high performance and robust real-time capability needs to be explored. Additionally, it may be possible to improve the overall model performance by leveraging the bilateral nature of an exoskeleton system. For example, in the case of transitioning to the next mode with a trailing limb, the contralateral leg's sensor information can aid the trailing limb's classification accuracy by starting to capture feature information about the next locomotion mode during the transition gait cycle.

Bayesian classifiers are a commonly used ML approach for mode classification due to their simplicity in translating to a real-time device [14,15]. Literature studies have shown different strategies to further improve the overall model accuracy by fusing gait time history information such as through a Dynamic Bayesian Network (DBN) that can reduce the steady-state error [16]. While these ML-based methods have been validated in different literature studies (e.g., robotic prostheses), the in-depth analysis of improving the ML model performance in continuous classification, especially in an exoskeleton application, has not been explored.

In this study, we conducted a human subject experiment where the user ambulated in a terrain environment consisting of different locomotion modes (i.e., level ground, ramps, and stairs) while wearing a robotic bilateral hip exoskeleton. Utilizing only the on-board mechanical sensor data during the experiment, we investigated varying complexity of Bayesian ML strategies (Naïve Bayes, Linear Discriminant Analysis, and Quadratic Discriminant Analysis) to train our mode classifier. The central hypothesis of this study is that utilizing the user's gait phase information as well as bilateral sensor information from the exoskeleton will improve the overall ML model accuracy. Additionally, we hypothesize that utilizing more complex Bayesian ML algorithms will improve the overall accuracy due to their strengths in maximizing the class separation. This study will provide meaningful information for the future exoskeleton developers as our study limits sensing to only mechanical sensors easily available within a commercial hip exoskeleton device [17]. Our research findings will help to create a high-level controller that can infer the user's environmental information to provide more optimal exoskeleton assistance.

II. Methods

A. Robotic Hip Exoskeleton

Our study utilized an autonomous bilateral robotic hip exoskeleton presented in our previous study (Fig. 1A) [18].

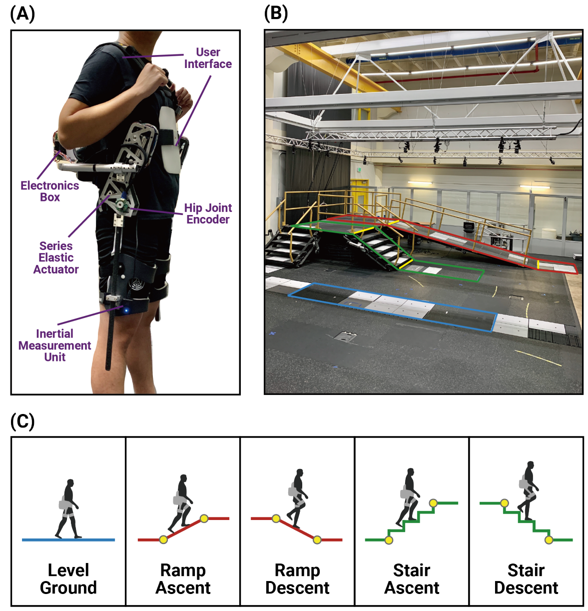

Fig. 1. (A) Robotic bilateral hip exoskeleton. Two symmetrically mounted IMUs and hip joint encoders measure the user's bilateral movement. (B) Terrain park utilized for the data collection. The platform height can be adjusted for different inclines. (C) Five specific ambulation modes for the classification task. Mode transition (yellow) points were defined as the initial heel contact of the next mode.

Briefly, the exoskeleton uses a series elastic actuator (SEA) at the hip joint for closed loop torque control in the sagittal plane. The exoskeleton houses several on-board mechanical sensors: an absolute magnetic encoder (Orbis, Renishaw, UK) measuring the user's hip joint angle and a 6-axis (accelerometer + gyroscope) inertial measurement unit (Micro USB, Yost Lab, USA) (IMU) measuring the user's thigh limb orientation. All sensors and actuators were controlled through an on-board microprocessor (myRIO, National Instruments, USA). All mechanical sensor data were sampled and recorded at 100 Hz. For this study, the exoskeleton used a zero impedance controller where the SEA mitigated residual interaction torque between the human and the exoskeleton with a residual RMS torque < 0.25 Nm.

B. Human Subject Data Collection

The study was approved by the Georgia Institute of Technology Institutional Review Board, and informed written consent was obtained for all subjects. Five able-bodied subjects with an age of 23.0 ± 2.1 years, height of 1.76 ± 0.08 m, and body mass of 74.3 ± 83.3 kg were asked to walk on an in-lab terrain park consisting of over ground ramps and stairs while wearing the robotic hip exoskeleton (Fig. 1B). The terrain park height was adjusted and set to four different stair heights (10.16 cm, 12.7 cm, 15.24 cm, and 17.78 cm) and ramp slopes (7.8°, 9.2°, 11.0°, and 12.4°) throughout the experiment. Each subject walked in 5 different locomotion mode conditions: level ground (LG), ramp ascent (RA), ramp descent (RD), stair ascent (SA), and stair descent (SD). For each mode (except for LG), the subject walked from LG to the desired mode and back to LG to allow for the inclusion

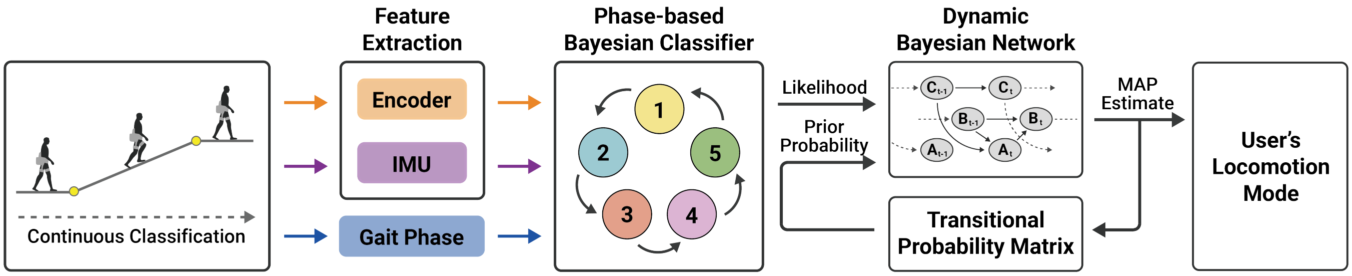

Fig. 2. Continuous locomotion mode classification strategy. Different features are extracted from mechanical sensors (encoder and IMU data) on the exoskeleton. The user's gait phase information is utilized to choose a relevant phase-based mode classifier during the gait cycle. The classifier's output of likelihood along with the prior probability in the Dynamic Bayesian Network computes the MAP estimate to classify the user's locomotion mode.

of different mode transitions (Fig. 1C). For a given incline level in each mode, the subject performed 8 trials where 4 trials the subject made the transitions with their left leg and 4 trials the subject made the transition with their right leg. Thus, a total of 128 trials were conducted per subject plus an additional set of 8 trials over flat level ground of similar length to the terrain trials. Throughout the experiment, the order of ramp and stair heights was randomized, and the exoskeleton was controlled in a zero impedance mode for all conditions. During all walking conditions, on-board bilateral mechanical sensor (hip joint encoder and thigh IMU) data were recorded.

C. Data Processing and Feature Extraction

To process the data to train the classifier, we defined the mode transition point as the initial heel contact of the next mode. Using the peak hip extension configuration (minimum hip joint angle during the gait cycle) as the gait segmentation point, we labeled the user's gait phase. Utilizing this information, we relabeled the data before/after the heel strike as the prior and posterior mode, respectively. Using the processed data, we followed a standard literature practice in the time domain for the feature extraction. Finalized features were minimum, maximum, mean, standard deviation, and latest value for a given window size [19].

D. Machine Learning Model Optimization

Three different Bayesian classifiers were implemented to classify the locomotion mode: Naïve Bayes (NB), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA) (Fig. 2). Bayesian classifiers have been well defined in the literature and have shown excellent performance in real-time implementation due to their simplicity, in particular LDA represents a gold-standard classifier for both upper and lower limb prosthetic applications [20,21]. We implemented these machine learning algorithms to train a user dependent model based on each subject's data. For all the model optimization processes, we conducted an 8-fold leave-one-trial-out validation for each subject where one trial from each type of trial was left in the testing set. Initially, we conducted a standard feature extraction window size sweep for each model. We varied the window size from 100 ms to 800 ms in increments of 50 ms sliding at a 10 ms rate. All three models showed similar trends and we finalized the feature window size to be 600 ms.

E. Phase Dependent Mode Classifier

Due to the non-stationary nature of the signals throughout the gait cycle, the extracted features can gradually change in a cyclical manner over the decision boundaries in the feature space. In order to mitigate such phenomenon, we segmented the signal data into different phases of the gait cycle. By doing so, we made the features lie more tightly to each other within a phase allowing the classifier to better draw the decision surfaces. We segmented the gait cycle into equal intervals, trained multiple models, and developed corresponding phase-based classifiers. To find the optimal number of classifiers within the gait cycle, we systematically swept through the different number of models for each algorithm (up to 8 models per gait cycle). We started with the feature window size of 600 ms and iteratively swept to ensure the optimal number of phase models and window size were converged.

F. Implementation of Dynamic Bayesian Network

Dynamic Bayesian Network (DBN) is a filtering technique used often in a time history-based classification leveraging a Markov assumption with a probabilistic representation (Fig. 2) [22]. At any point in time, DBN calculates the maximum a posteriori (MAP) estimate from a posterior probability, $P(C|\vec{x})$ (Eq. 1).

$$\hat{C}_{MAP} = argmax(P(C|\vec{x})) \tag{1}$$

Posterior probability is computed by taking the Hadamard product of the classifier's likelihood, $P(\vec{x}|C)$, and the prior probability, $P(C)$ (Eq. 2).

$$P(C|\vec{x}) = \frac{P(\vec{x}|C) \circ P(C)}{P(\vec{x})} \tag{2}$$

Current time step's prior probability is calculated based on the previous time step's posterior probability and the transition probability matrix, Φ, learned from the training data set (Eq. 3).

$$P(C)_t = P(C|x)_{t-1} \times \Phi \tag{3}$$

The final classified mode is the class with the maximum posterior probability. We trained the DBN using the same training data set used for training each classifier.

G. Model with Unilateral and Bilateral Features

To analyze the effect of leveraging the bilateral nature of the hip exoskeleton, we investigated the effect of adding the contralateral leg's feature information when training the classifier. Utilizing feature information from the other side can improve the overall model performance especially during the transition gait cycle. We evaluated the model performance by calculating the model's steady-state error and mode transitional error. Additionally, we analyzed the unilateral and bilateral model performances by differentiating the testing trials into leading and trailing trials for each leg and calculating the steady-state and transitional error.

H. Statistical Analysis

We conducted a three-way repeated measures analysis of variance (ANOVA) to compare the model performance across all conditions (α = 0.05). A Bonferroni *post-hoc* correction for a multivariate analysis was used to compute the statistical differences between each condition (SPSS Statistics 21.0, IBM, USA).

III. Results

A. Phase Dependent Mode Classifier

For all models, similar trends were shown where the overall classification error converged after 5 phase models. Iterative results indicate that the overall model architecture was optimal with a 600 ms window size (same size as the initial window size sweep) with 5 models within the gait cycle (Fig. 3). Across all algorithms, using 5 phase models reduced the relative classification errors by 35.62 $\pm$ 10.01% compared to the 1 phase model ($p < 0.05$).

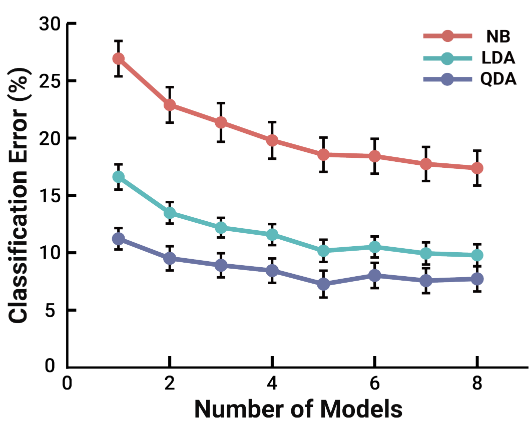

Fig. 3. Phase dependency model sweep results. 5 phase models with 600 ms feature window size were shown to be the optimal number of models for maximal classification performance across all ML algorithms.

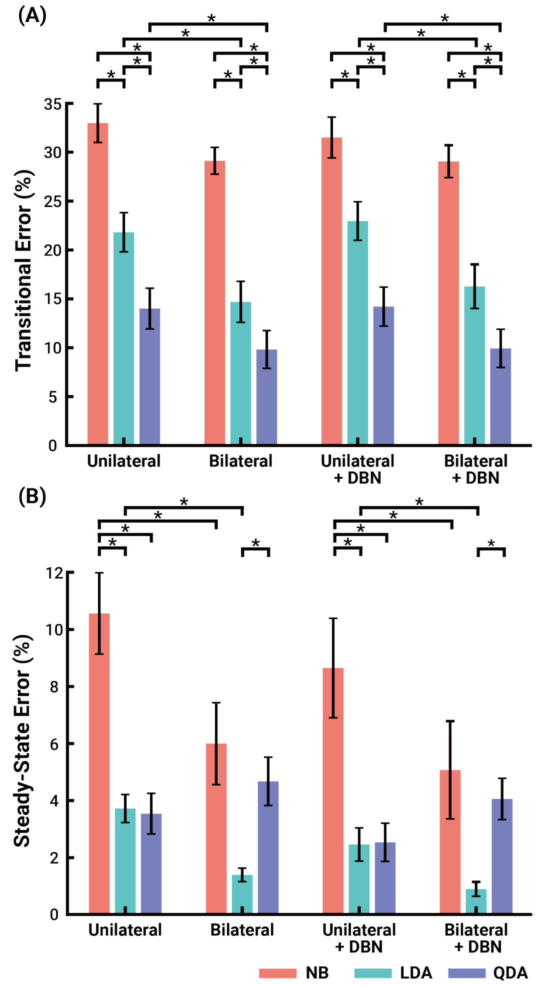

Fig. 4. Locomotion mode classifier performance for Naïve Bayes (red), Linear Discriminant Analysis (green), and Quadratic Discriminant Analysis (purple) evaluated in (A) transitional and (B) steady-state classification error. Error bars represent $\pm$ 1 SEM and asterisks indicate statistical significance ($p < 0.05$).

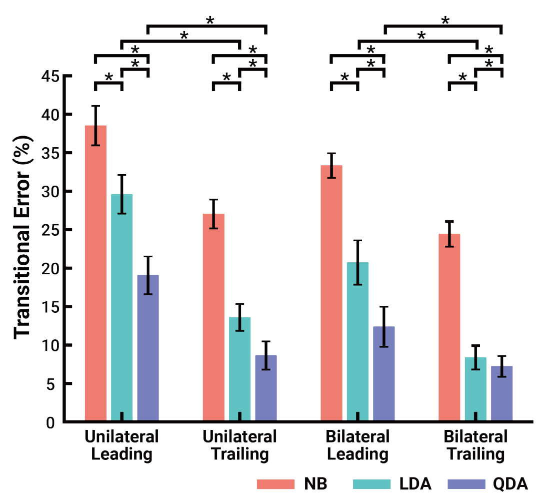

Fig. 5. Unilateral and bilateral feature-based model performance for Naïve Bayes (red), Linear Discriminant Analysis (green), and Quadratic Discriminant Analysis (purple) during the transition gait cycle. Transitional error was evaluated into two conditions where the classifier's leg was either leading/trailing during the transition gait cycle. Error bars represent $\pm$ 1 SEM and asterisks indicate statistical significance ($p < 0.05$).

B. Overall Algorithm Performance

For all conditions, QDA reduced the relative transitional errors by 61.74 ± 13.38% and 36.99 ± 13.92% compared to NB and LDA, respectively ($p < 0.05$) (Fig. 4A). Across all conditions, LDA reduced the relative transitional errors by 41.50 ± 14.60% compared to NB ($p < 0.05$). Across all models, models with DBN reduced the relative steady-state errors for both unilateral and bilateral feature conditions by 26.79 ± 8.00% and 21.49 ± 12.48% compared to models without DBN, respectively ($p < 0.05$), while no statistical differences were shown in transitional errors.

NB and LDA using bilateral features reduced the relative steady-state errors by 53.73 ± 19.19% compared to using unilateral feature information ($p < 0.05$) while QDA did not show any statistical difference between the two conditions ($p = 0.153$) (Fig. 4B). Similarly, LDA and QDA using bilateral features reduced the relative transitional errors by 33.72 ± 14.52% compared to using unilateral feature information ($p < 0.05$). All models during the trailing limb condition had an average of 42.91 ± 18.98% lower transitional errors than the models during the leading limb condition ($p < 0.05$) (Fig. 5).

IV. Discussion

Our study explored three key features in enhancing the locomotion mode classification performance using different ML algorithms for a robotic hip exoskeleton: 1) configuring the optimal number of ML models within the gait cycle, 2) comparing different complexity of Bayesian classifier performance, and 3) evaluating the effect of using unilateral vs. bilateral feature information. Along with these key features, implementing DBN further improved the ML model performance by reducing the relative steady-state errors by 24% across models ($p < 0.05$) and had no significant effect on transitional errors.

First, we accept the hypothesis that increasing the number of ML models within the gait cycle does improve the overall mode classification accuracy which was shown consistently across all three classifier types. The optimal number of models to be used within the gait cycle was 5. Interestingly, this optimal phase number is relevant to the gait phase segmentation from a gait biomechanics perspective which correlated closely to stance/swing phase dynamics (e.g., 3 models in stance and 2 models in swing phase).

Second, we explored the effect of model complexity in the overall classifier's performance. For both unilateral and bilateral feature conditions, each step of model complexity yielded significantly better transitional error results. However, similar trend was not exhibited in the steady-state error results. Mainly, QDA using bilateral features increased the steady-state error compared to QDA using unilateral features. This may be due to the "curse of dimensionality" [23] that the number of features provided to the QDA model was not backed by the size of the data set which can cause the model to overfit. While it was outside the scope of this study, it is possible that future studies with robust feature selection optimizations to reduce the dimensionality could benefit the QDA algorithms in the case of the bilateral sensors which have a feature dimension of 70. Therefore, we reject the hypothesis that increasing the model complexity does not yield better performance, but rather, there is an optimal level of complexity in the ML algorithm that can maximize the classification accuracy. This study indicates that the LDA algorithms again represent the right level of complexity for Bayesian mode classification, similar to many results in the literature for locomotion mode classification [24,25].

Lastly, we accept the hypothesis that utilizing the bilateral feature information can further improve the ML model's performance. Our result showed that fusing bilateral features can reduce the overall classification error rate by 43% which aligns with a relevant literature study that used a full lower-limb neuromechanical signals from able-bodied subjects yielding a 32% error rate reduction [25]. Our leading/trailing analysis indicates that utilizing the contralateral leg's feature information can help the ML model to improve the performance during the transitional gait cycle. This is mainly due to the contralateral leg providing meaningful information (in the trailing limb situation) as it will have already transitioned into the next mode.

Our continuous mode classifiers showed comparable results to relevant literature studies. Huang *et al.* implemented a continuous phase-based algorithm to a robotic prosthesis and showed approximately 1% steady-state error during the stance phase and 5% during the swing phase [6]. However, our models showed consistent performances (our best performing model has less than 1% steady-state error) regardless of where the user is in during the gait cycle. Long *et al.* achieved an error of 4% for a full lower-limb exoskeleton [11]. However, the study utilized several distal mechanical sensors (e.g., 6 ground reaction force sensors) which may not be accessible for a robotic hip exoskeleton. Currently, the state-of-the-art locomotion mode classifier for a robotic hip exoskeleton has 3% classification error [12]. One of the main limitations of this study was the model's capability in classifying once per gait cycle. Additionally, the study was limited that the model only classified stair and level ground modes. Our comparable result (only testing on level ground and stair modes) to this study outperformed with an error of 1.3%. Our study expanded from these limitations and illustrated the feasibility of classifying continuously in all five ambulation modes.

One limitation of our study is the limited number of subjects (N=5). Low subject number limited our capability of investigating our model performance and associated statistical results. Another limitation of our study is that our study mainly focused on the device data collected during a zero impedance mode. Our previous studies indicate that depending on the exoskeleton's assistance level, user's gait dynamics can change [26,27]. This can potentially create variance in the sensor signals, which may affect the classifier's accuracy. Additionally, as our study only investigated an able-bodied subject's data set, the effect of asymmetric gait (e.g., hemiplegic gait due to stroke) on the mode classifier is unknown. Future studies should include sensor data with different types of exoskeleton assistance and gait pattern to train a more robust ML model. Lastly, our study was limited that it was an offline analysis. Literature studies indicate that real-time mode classification can have an effect on mode classification error which is not accounted for in offline analyses [20]. Therefore, ML model performance validation in real-time implementation is needed for future studies.

V. Conclusion

Our study investigated ML strategies for improving the continuous locomotion mode classification for a robotic hip exoskeleton. We found that using an optimal number of classifiers during the gait cycle can reduce the classification error up to 35% compared to using a single model. Moreover, our results showed that leveraging the contralateral leg's sensor information can further improve the classifier's performance by 43% compared to using only the ipsilateral leg's sensor data. Our approach validated the feasibility of utilizing only the on-board mechanical sensors on the exoskeleton to accurately and continuously classify the user's locomotion mode in a bilateral robotic hip exoskeleton. Future work can utilize our findings and translate the locomotion mode classifier to a real-time control of the powered hip exoskeleton.

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