Predicting walking response to ankle exoskeletons using data-driven models

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I. Keywords

Ankle exoskeleton; data-driven modeling; locomotion; prediction; joint kinematics; muscle activity

II. Abstract

Despite recent innovations in exoskeleton design and control, predicting subject-specific impacts of exoskeletons on gait remains challenging. We evaluated the ability of three subject-specific phase-varying models to predict kinematic and myoelectric response to ankle exoskeletons during walking, without knowledge of specific user characteristics. Each model – a purely phase-varying (PV), linear phase-varying (LPV), and nonlinear phase-varying (NPV) model – leveraged Floquet Theory to predict deviations from a nominal gait cycle due to exoskeleton torque, though the models differed in structure and expected prediction accuracy. For twelve unimpaired adults walking with bilateral passive ankle exoskeletons, we predicted kinematics and muscle activity in response to exoskeleton torque. Prediction accuracy of the LPV model was better than the PV model when predicting less than 12.5% of a stride in the future and explained 55–70% of the variance in hip, knee, and ankle kinematic responses to torque. The LPV model also predicted kinematic responses with similar accuracy to the more-complex NPV model. Myoelectric responses were challenging to predict across models, explaining at most 10% of the variance in responses. This work highlights the potential of linear phase-varying models to predict complex responses to ankle exoskeletons and inform device design.

III. Introduction

Ankle exoskeletons are used to improve kinematics and reduce the energetic demands of locomotion in unimpaired adults and individuals with neurologic injuries [1-6]. Customizing exoskeleton properties to improve a particular individual's gait is challenging and accelerating the iterative experimental process of device optimization is an active area of research [7, 8]. Studies examining the effects of exoskeleton properties – sagittal-plane ankle stiffness or equilibrium ankle angle for passive exoskeletons and torque control laws for powered exoskeletons – on kinematics, motor control, and energetics, have developed exoskeleton design principles to reduce the energetic demand of walking and improve the quality of gait [1, 5, 7, 9, 10]. However, predicting how an individual will respond to an ankle exoskeleton remains challenging for both unimpaired individuals and those with motor impairments [2, 11, 12].

Common physics-based approaches to predicting ankle exoskeleton impacts on gait, including simple mechanical models and more physiologically-detailed musculoskeletal models, use first-principles in physics and biology to analyze and predict exoskeleton impacts on gait. For example, one lower-limb mechanical walking model predicted that an intermediate stiffness in a passive exoskeleton would minimize the energy required to walk; a finding that was later observed experimentally in unimpaired adults [1, 13]. While this model's structure permitted interpretation of kinematics and mechanical energetics, it did not predict myoelectric responses to the exoskeletons. More physiologically-detailed musculoskeletal models have been used to predict the impacts of exoskeleton design on muscle activity during walking in children with cerebral palsy and running in unimpaired adults [14, 15]. While these studies identified hypothetical relationships between kinematics and the myoelectric impacts of exoskeleton design parameters, sensitivity to musculotendon properties likely limited the specificity of their predictions [16, 17].

Challenges to accurately predicting responses to ankle exoskeletons with physics-based models largely stem from uncertainty in adaptation, musculoskeletal physiology, and motor control, which may vary between

individuals and influence response to exoskeletons. One study found that, while individuals explore different gait patterns to identify an energetically-optimal gait, exploration does not always occur spontaneously, resulting in sub-optimal gait patterns for some users [18]. Popular physiologically-detailed models of human gait typically assume instantaneous and optimal adaptation, which do not reflect how experience and exploration may influence an individual's response to exoskeletons, possibly reducing the accuracy of predicted responses [19, 20]. Additionally, when specific measurement sets are unavailable for model parameter tuning, models use population-average based assumptions about musculoskeletal properties and motor control [17, 18, 20-22]. However, musculoskeletal properties and motor control are highly uncertain for individuals with motor impairments, today's most ubiquitous ankle exoskeleton users [21-24]. Musculotendon dynamics and motor complexity are known to explain unintuitive exoskeleton impacts on gait energetics, suggesting that uncertain musculotendon parameters and motor control may limit the accuracy of predicted changes in an individual's gait with ankle exoskeletons [16, 17, 23]. Predictions of exoskeleton impacts on gait using physiological models may, therefore, require accurate estimates of adaptation, musculotendon parameters, and motor control, which can be resource and time-intensive to obtain.

Data-driven models provide an alternative approach to handling uncertainty in user-exoskeleton dynamics. Human-in-the-loop optimization provides a model-free alternative to physics-based prediction of exoskeleton responses by automatically exploring different exoskeleton torque control strategies for an individual [7, 8]. This experimental approach requires no prior knowledge about the individual: optimization frameworks identify torque control laws that minimize metabolic rate for an individual using only respiratory data and exoskeleton torque measurements. However, the process is resource- and time-intensive, taking hours to complete. In a clinical context where data collection time is limited, machine learning algorithms trained using retrospective datasets have been used to predict changes in gait in response to different ankle exoskeleton (ankle-foot orthosis) designs in children with cerebral palsy [9]. This study used the Random

Forest Algorithm with gait analysis and clinical exam data to predict changes in joint kinematics with different orthosis designs, reporting good classification accuracy and modest accuracy of predicted changes in kinematics. Unlike physiologically-detailed or physics-based models, human-in-the-loop optimization and Random Forest models are challenging to interpret, limiting insight into how a specific individual's physiology influences response to exoskeleton torque. A balance between physiologically-detailed physics-based and model-free data-driven approaches may facilitate the prediction and analysis of responses to ankle exoskeletons without requiring extensive knowledge of the underlying system.

In this work, we use a model-based data-driven framework, focusing specifically on phase-varying models, to predict responses to ankle exoskeletons. Phase-varying models typically have linear structure whose parameters are estimated from data, potentially enabling both prediction and analysis of gait with exoskeletons [25, 26]. Similar to other data-driven modeling approaches, phase-varying models do not require knowledge of the physics or control of the underlying system: the user's physiological characteristics or adaptation strategy in the context of walking with exoskeletons. Phase-varying models leverage dynamical properties of stable gaits derived from Floquet Theory, which ensures that the convergence of a perturbed trajectory to a stable limit cycle may be locally approximated using time-varying linear maps [27]. Similar principles have been shown to generalize to limit cycles in non-smooth or hybrid systems, such as human walking [28]. Moreover, phase-varying modeling principles have been applied to biological systems, identifying linear phase-varying dynamics to investigate gait stability and predict changes in kinematics in response to perturbations [25, 26, 29-31]. Similarly, responses to ankle exoskeletons torques may be defined as perturbations off an unperturbed (*i.e.* zero torque) gait cycle, suggesting that the principles of phase-varying models will generalize to walking with exoskeletons. To the best of our knowledge, phase-varying models have never been used to study walking with exoskeletons and the extent to which the principles underlying phase-varying models of locomotion generalize to walking with exoskeletons is unknown.

To determine if phase-varying models represent useful predictive tools for locomotion with exoskeletons, the purpose of this research was to evaluate the ability of phase-varying models to predict subject-specific kinematic and myoelectric responses to ankle exoskeleton torque during walking. We evaluated responses to exoskeletons in unimpaired adults walking with passive ankle exoskeletons under multiple dorsiflexion stiffness conditions. We focused on three related classes of phase-varying models with different structures, complexity, and expected prediction accuracies: a phase-varying (PV), a linear phase-varying (LPV), and a nonlinear phase-varying (NPV) model. According to Floquet Theory and prior modeling of human gait without exoskeletons, we expected the LPV model to accurately predict responses to passive exoskeleton torque [25-27, 29]. While nonlinear responses to torque may be harder to locally approximate using a linear model compared to a nonlinear model when deviations from the unperturbed gait cycle are large, passive exoskeletons typically elicit small changes in joint kinematics and muscle activity [1, 2]. We, therefore, hypothesized that the LPV models would predict gait kinematics and myoelectric responses to torque more accurately than the PV model and as accurately as the NPV model. To further exemplify the potential utility of phase-varying models in gait analysis with ankle exoskeletons, we show how varying the length of model prediction windows may inform measurement selection for exoskeleton design and analysis. To assess the viability of data-driven phase-varying models in time-constrained gait analysis settings, we evaluated the effect of limiting the size of the training dataset on prediction accuracy.

IV. Methods

A. Experimental protocol

We collected kinematic and electromyographic (EMG) data from 12 unimpaired adults (6 female / 6 male; age = 23.9 ± 1.8 years; height = 1.69 ± 0.10 m; mass = 66.5 ± 11.7 kg) during treadmill walking with bilateral passive ankle exoskeletons at self-selected speed. Each participant performed two sessions on separate days within a one-week span. In the first session, we modified the exoskeletons for fit and comfort and performed a 20-minute practice session (*see Supplemental – S1*).

Data were collected during the second session. We monitored changes in kinematics using a modified Helen-Hayes marker set [32] and a 10-camera motion capture system (Qualisys AB, Gothenburg, SE) and measured muscle activity using 14 wireless EMG sensors (Delsys Inc., Natick, USA). The EMG sensors were placed bilaterally on the soleus, medial gastrocnemius, tibialis anterior, vastus medialis, rectus femoris, lateral hamstrings, and the gluteus medius following SENIAM guidelines [33]. Participants performed four randomized trials on a split-belt instrumented treadmill (Bertec Corp., Columbus, USA) under different exoskeleton conditions (Fig. 1). The passive exoskeletons used in this study generated ankle plantarflexion torques as a function of the user's ankle angle, and the exoskeleton's neutral angle and rotational stiffness. The four conditions were set to sagittal-plane stiffness values: K_0 (0 Nm/deg), K_1 (1.17 Nm/deg), K_2 (3.26 Nm/deg), and K_3 (5.08 Nm/deg), a range known to alter kinematics and myoelectric signals during gait (Fig. 1) [1]. Unlike many clinical exoskeletons (ankle-foot orthoses), whose torque profiles are smooth functions of ankle angle, the torque profiles of the exoskeletons used in this work were piecewise-smooth functions of ankle angle and did not resist plantarflexion, similar to other experimental devices [1, 3]. Participants walked for six minutes per trial, the last four of which were recorded, and could rest between trials.

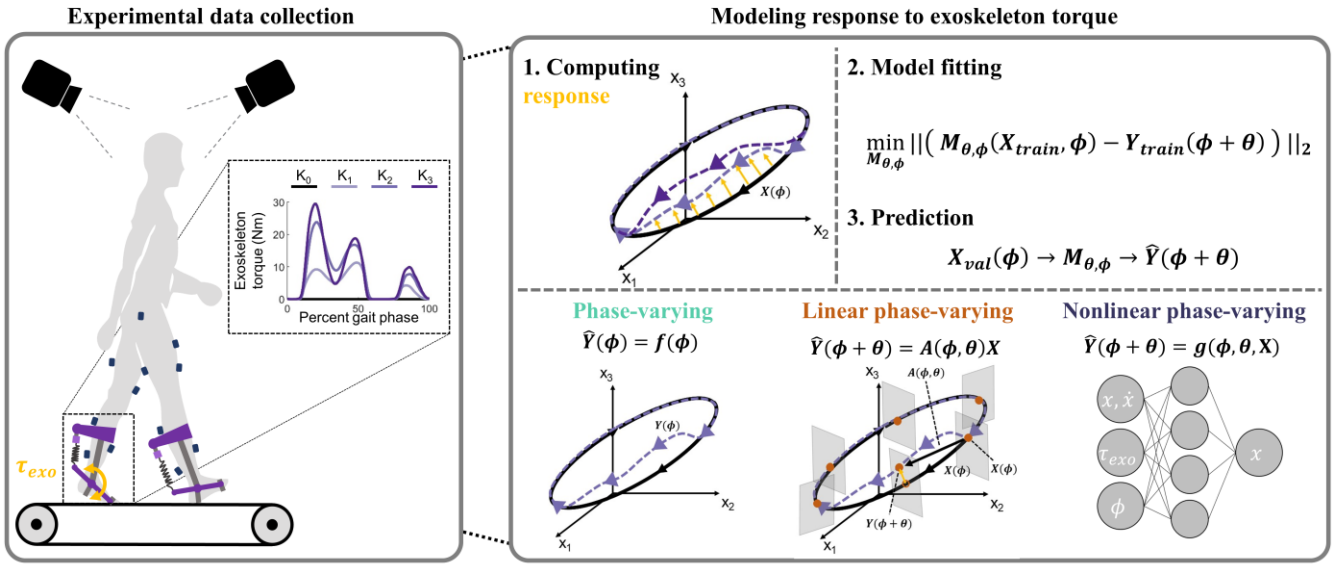

Fig. 1. <u>Left box</u>: Data were collected during treadmill walking with bilateral ankle exoskeletons that used linear springs to resist dorsiflexion. Increasing exoskeleton stiffness (K_0–K_3) increased exoskeleton torque (τ_{exo}, yellow). <u>Right box</u>: (1) Purple dashed arrows represent responses to exoskeleton torque, which were defined as deviations from the average zero-torque gait cycle (K_0). (2) Response data from the training set were used to fit each model. (3): Models were validated by predicting responses from the held-out torque condition using the models fit in (2). <u>Right box (bottom)</u>: The three phase-varying models were fit and evaluated on the same training and validation sets.

A = linear function; f, g = nonlinear functions; $M_{\theta,\phi}$ = generic model function of prediction window and phase; τ_{exo} = exoskeleton torque; X = experimental inputs; Y = experimental outputs; $\hat{Y}$ = predicted outputs; ϕ = phase; θ = prediction window.

The marker trajectories were low-pass filtered at 6 Hz using a zero-lag fourth-order Butterworth filter [6]. We computed joint kinematics by scaling a generic 29 degree-of-freedom skeletal model to each participant's skeletal geometry and body mass using the inverse kinematics algorithm in OpenSim 3.3 to convert marker trajectories into joint kinematics [19, 34]. To compute linear EMG envelopes, we high-pass filtered the EMG data at 40 Hz, rectified the data, and low-pass filtered at 10 Hz [10]. Kinematic and EMG data were pre-processed using custom scripts in MATLAB (MathWorks, Natick, USA).

B. Gait phase and phase-varying models

Unlike the typical gait cycle definition – the percentage of time between successive foot contact events – we used a gait phase based on kinematic posture, which we expected to improve predictions of a system's response to perturbations from the exoskeletons [35]. Using posture-based gait phase groups kinematically-

similar measurements at a specific phase, reducing variance in the data at any point in the cycle, and ensuring that similar postures across exoskeleton conditions are used during model fitting and prediction. Moreover, Floquet Theory ensures that phase is well-defined using any periodically-varying measurements [27]. We used the *Phaser* algorithm, which estimates a system's phase using arbitrary input signals considered to be phase-locked, to generate *gait phase* estimates as a function of kinematic posture [30]. We selected left and right leg hip flexion angles as phase variables, similar to a phase variable proposed to control robotic prostheses [35].

1) Phase-varying model

The phase-varying (PV) model was our simplest model and predicts outputs purely as a function of gait phase. Rather than taking exoskeleton torque as an input, PV model predictions are similar to simply guessing the average of the training data at a certain gait phase (Table I) [30, 36]. The PV model takes a phase estimate as an input and returns a prediction of the system's output variables, $\hat{Y}_{\phi} \in \mathbb{R}^{M}$, where M is the number of outputs. The PV model was parameterized using a seventh-order Fourier Series as a function of phase. Since the PV model is purely a function of phase, it served as a lower bound on prediction accuracy.

2) Linear phase-varying model

The linear phase-varying (LPV) model is a discrete-time model that predicts system outputs at a future, based on measurements at an initial phase (Table I). For any phase, ϕ, from 0-100% of a stride and a prediction window of size θ, the LPV model returns the matrix $A_{\phi,\theta} \in \mathbb{R}^{M \times N+1}$, denoting the map from the initial phase to the final phase, where $N + 1$ denotes the number of input variables (N) plus a constant term. At 64 initial phases spaced equally over the gait cycle, we fit discrete maps between initial and final phases using weighted least-squares regression [25, 26, 29]. We weighted each observation based on the proximity of its phase estimate to the phase prescribed at each initial phase using a Gaussian weighting scheme. For each prediction window, the LPV model was represented as a continuously phase-varying function, $F_{LPV,\theta}(\phi) = A_{\phi,\theta} +$

$error$, parametrized by a Fourier Series. We expected the LPV model's prediction accuracy to exceed that of the PV model [27].

3) Nonlinear phase-varying model

While the LPV model should approximate nonlinearities in the dynamics of response to exoskeleton torque, we used a nonlinear phase-varying (NPV) model as an upper bound on prediction accuracy. Specifically, we used a three-layer feedforward neural network – a universal function approximator – to achieve an upper limit on prediction accuracy, provided enough training data (Table I) [37]. Neural networks are considered state-of-the-art predictors and are used in numerous domains, including image recognition and robotics [38]. The NPV model's parameters were tuned for each prediction window and included phase as an input. We expected the NPV model's prediction accuracy to meet or exceed that of the LPV model. Additional technical detail for all models can be found in the *Supplemental – S1*.

Table I: Summary of model structures and expected prediction accuracies.

Model	Functional form	Linear terms	Nonlinear terms	Expected prediction accuracy
Phase-varying (PV)	$\hat{Y}_{\phi} = F_{PV}(\phi)$	None	Phase	Low
Linear phase-varying (LPV)	$\hat{Y}_{\phi+\theta} = F_{LPV,\theta}(\phi)X_{\phi}$	Inputs	Phase	Moderate
Nonlinear phase-varying (NPV)	$\hat{Y}_{\phi+\theta} = G_{NPV,\theta}(\phi, X_{\phi})$	None	Phase Inputs	Moderate-High

F = model functions parameterized by a Fourier Series; G = feedforward neural network model; ϕ = phase; θ = prediction window; X = input data; $\hat{Y}$ = predicted outputs

C. Inputs and output variable selection

To reflect clinically-relevant measurements and the dynamics of the neuromusculoskeletal system, we selected input variables expected to encode musculoskeletal dynamics and motor control: 3D pelvis orientation and lower-limb and lumbar joint angles, processed EMG signals, and their time derivatives at an initial phase, ϕ [1, 39]. To include information sufficient to parameterize exoskeleton torque profiles between

initial and final phases, we appended ten time-history exoskeleton torque samples per leg – uniformly distributed between the initial and final phases – to the inputs, resulting in $N = 80$ inputs [7, 12]. The outputs ($M = 20$) included right and left leg sagittal-plane hip, knee and ankle kinematics, and EMG signals from each muscle at a final phase, $\phi + \theta$, offset from the initial phase by prediction window θ. We modeled response to exoskeleton torque as the deviation from the unperturbed gait cycle (*i.e.* the zero-stiffness, K_0 condition), by subtracting the phase-averaged zero-torque gait cycle from each exoskeleton condition [26, 29]. All data were de-meaned and scaled to unit variance of the training set.

We computed each model's ability to predict responses to torque *within* the range of exoskeleton stiffness levels used to train the models (interpolation) by training each model using the K_0, K_1 and K_3 datasets and validating on the held-out K_2 dataset. While predicting *beyond* the range of exoskeleton stiffnesses included in the training set (extrapolation) would present an interesting test case, it is beyond the scope of this work. During validation, experimental output data from the K_2 condition were compared to the corresponding model predictions. We used the same training and validation sets for all models.

We quantified each model's prediction accuracy using the relative remaining variance (RRV) of model predictions compared to the experimental validation data [25]. The RRV is calculated as the ratio of the variance of the prediction error and the variance of experimental data. An RRV value of zero implies a perfect prediction, while unity RRV values can be achieved by predicting the mean of the validation data. Since we de-meaned the data and predicted deviation from the zero-torque condition, RRV values below unity indicate that predictions are more accurate than guessing zero response to exoskeleton torque. We computed RRV values for each output using a bootstrapping procedure with 200 iterations [25]. We computed RRV values for each model over the entire validation time series of approximately 240 strides. During analysis, the right and left leg RRV values for each output variable were averaged, as we expected nearly symmetric responses from unimpaired participants.

We additionally evaluated the LPV and NPV models' prediction accuracies over a range of prediction windows, between 6.3 and 100% of a gait cycle, in increments of 6.3%. When optimizing exoskeleton torque profiles, predicting response from measurements at an initial phase (e.g. initial contact of the foot with the ground) to achieve a desired outcome at some final phase may be of interest, such as improving midstance knee kinematics in children with cerebral palsy [2, 3]. However, as prediction window length increases, coherence between measurements at initial and final phases decreases due to nonlinearities in musculoskeletal dynamics [39-41]. The loss of coherence with increasing prediction window should result in prediction accuracies reducing to that of predicting the average response, rather than stride-specific responses. For measurements exhibiting small and variable responses to exoskeleton torque, prediction accuracy at large prediction windows should be similar to those of the PV model. Identifying the maximum prediction window at which initial measurements improve predictions at a final phase may inform exoskeleton control laws or design criteria. Therefore, we identified the largest prediction window lengths at which RRV values were significantly less than those of the PV model, which were constant across prediction windows.

The amount of data required to accurately predict response to exoskeletons will restrict the settings in which phase-varying models may be practical, such as in clinical gait analysis where datasets typically contain only a small number of gait cycles [2, 9]. We quantified the impact of training set size on prediction accuracy by determining the amount of training data needed for RRV values to approach their values when models were trained using the entire training set (RRV_{min}). We iteratively reduced the training set size by 10% of the full training set size (approximately 24 strides per exoskeleton condition), removing data from the end of each torque condition in the training set, providing a range of 24-240 strides of training data per condition. For all training set sizes, we evaluated models using the full-length validation set.

To identify differences in performance between the three models, we identified differences in the models' average prediction accuracies using repeated-measures analysis of variance tests at a significance level of $\alpha = 0.05$. When significant differences between models emerged, we identified pair-wise differences between models using post-hoc paired t-tests ($\alpha = 0.05$) and a Holm-Sidak step-down correction for multiple comparisons [10, 42]. We report percent reductions in RRV values compared to the PV model and percent differences between the LPV and NPV models.

V. Results

Exoskeleton stiffness had the largest impact on ankle kinematics, smaller impacts on knee and hip kinematics, and variable impacts on muscle activity (Fig. 2). Compared to the K_0 condition, the peak ankle dorsiflexion angle during single-limb support decreased significantly in the K_2 (36.7%) and K_3 (40.0%) conditions ($p < 0.020$). Average integrated EMG increased slightly, but not significantly in the hamstrings and tibialis anterior ($p > 0.066$) in the K_2 and K_3 conditions compared to the K_0 condition.

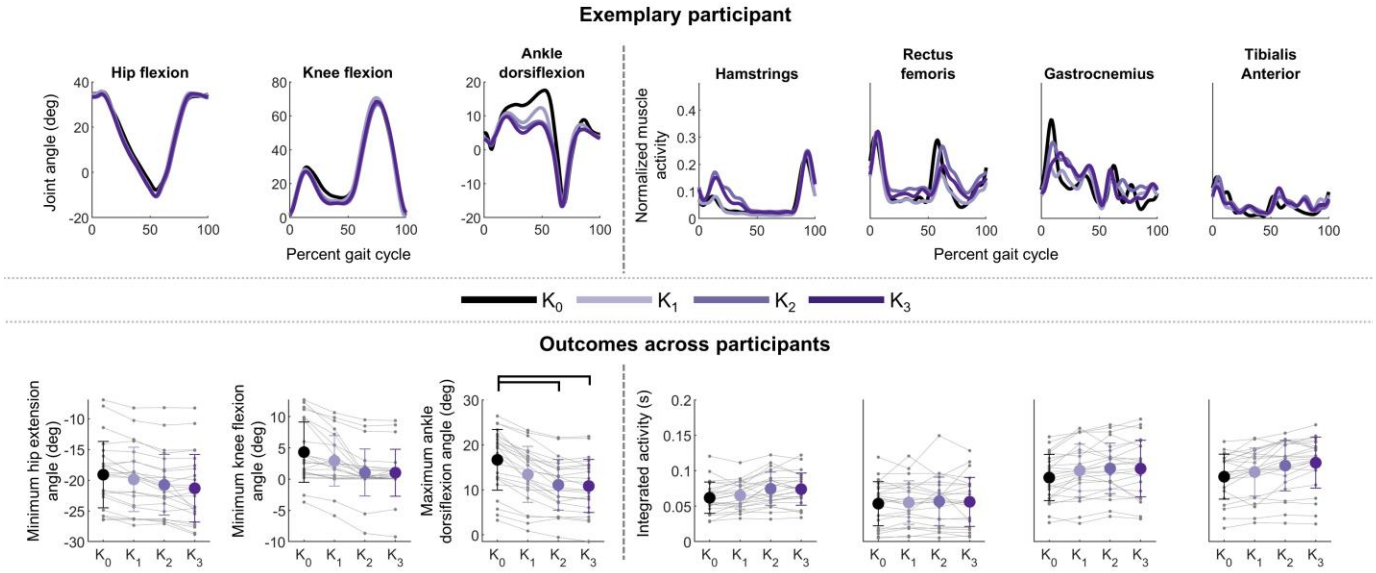

Fig. 2. <u>Top</u>: Average kinematic (left) and EMG (right) data for one participant who exhibited large, repeatable responses to exoskeleton torque and high model prediction accuracies (P03). Black lines show the zero-torque condition (K_0) that was subtracted from all conditions to reflect responses to exoskeleton torque. <u>Bottom</u>: Average (±1SD) kinematic and myoelectric responses for all participants in each torque condition. Brackets denote significant differences between exoskeleton conditions according to post-hoc paired t-tests ($\alpha = 0.05$) and a Holm-Sidak step-down correction. Thin gray lines represent individual legs.

All three models predicted kinematic but not myoelectric responses to exoskeleton torque (RRV < 1; Fig. 3; Table II). At the second shortest prediction window ($\theta = 12.5\%$), the LPV model's prediction accuracy at the ankle – where the largest responses to torque were observed – was 41.6 ± 16.0% more accurate than the PV model ($p < 0.001$) and was not significantly different than the NPV model ($p = 0.48$). Similarly, the LPV model's prediction accuracy at the hip was 41.7 ± 12.7% ($p < 0.001$) better than the PV model and did not differ from the NPV model at the hip or knee ($p > 0.105$). However, as prediction window length increased, LPV and NPV model prediction accuracies of all outputs except the ankle approached those of the PV model. Changes in knee and hip kinematics were predicted more accurately than the baseline PV model for prediction windows shorter than $\theta = 18.8\%$ of a stride ($p < 0.001$) in the LPV model and $\theta = 12.5\%$ of a stride ($p < 0.001$) in the NPV model (Fig. 4). At the ankle, the LPV model predicted kinematics 29.1–60.0% more accurately than the PV model for all prediction windows ($p < 0.001$). The NPV model's predictions were similar to the LPV model but were not significantly better than those of the PV model for $12.5\% < \theta < 37.5\%$ and $68.8\% < \theta < 93.7\%$ of a stride ($p < 0.001$).

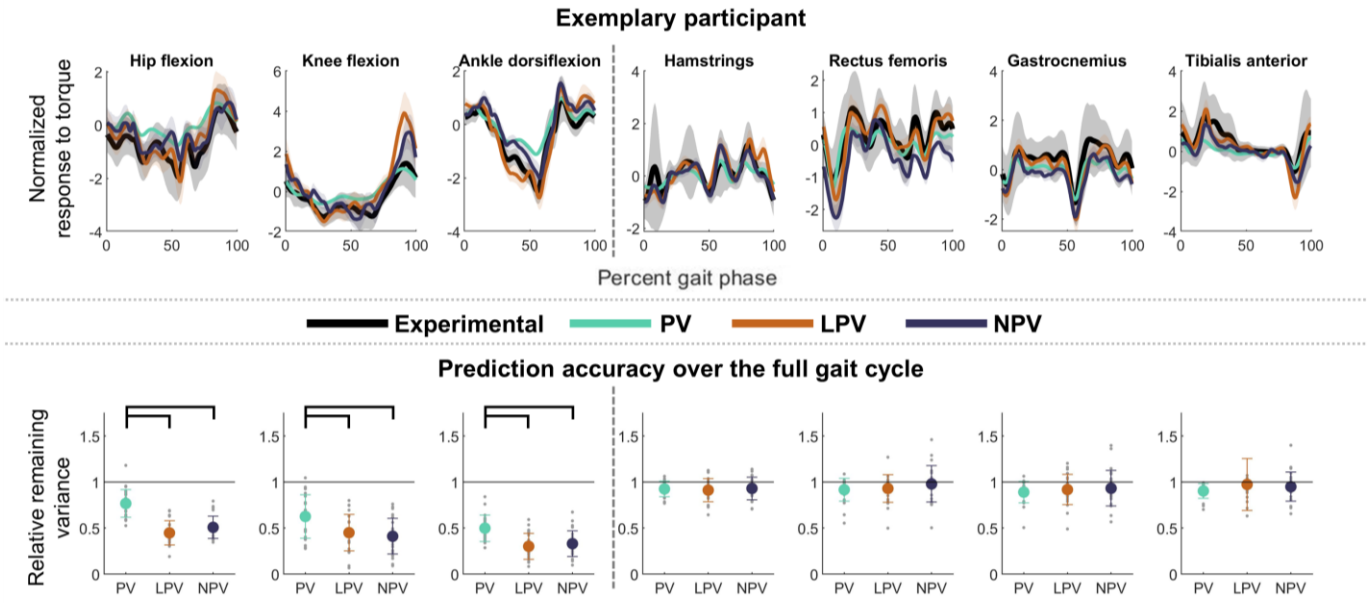

Fig. 3. <u>Top</u>: Average (±1SD; shaded region) kinematic and myoelectric experimental (black) and predicted responses to torque, at a prediction window of θ = 12.5% of a stride, for one participant who exhibited large responses to the exoskeletons (P03). Predictions were performed using data from the held-out K_2 condition. Full joint trajectories may be reproduced by rescaling and adding the average unperturbed gait cycle to the predictions. <u>Bottom</u>: Average (±1SD) prediction accuracies for all participants. Gray dots represent individual legs. Brackets denote significant differences between models. Kinematic predictions for the LPV (orange) and NPV (purple) models were significantly more accurate than those of the PV model (green). The LPV and NPV models exhibited similar prediction accuracy for all outputs. Myoelectric responses were poorly predicted by all models.

Table II: Average (± 1SD) RRV values for kinematic and myoelectric predictions at a 12.5% prediction window

Output	PV	LPV	NPV
Ankle angle†‡	0.50 ± 0.14	0.30 ± 0.14	0.33 ± 0.14
Knee angle†‡	0.62 ± 0.24	0.45 ± 0.20	0.41 ± 0.19
Hip angle†‡	0.77 ± 0.15	0.44 ± 0.13	0.51 ± 0.12
Tibialis anterior	0.90 ± 0.08	0.97 ± 0.28	0.95 ± 0.15
Soleus	0.86 ± 0.21	1.02 ± 0.66	1.04 ± 0.64
Gastrocnemius	0.89 ± 0.12	0.91 ± 0.16	0.93 ± 0.19
Vastus medialis	0.92 ± 0.12	0.93 ± 0.15	0.98 ± 0.20
Rectus femoris	0.87 ± 0.21	0.91 ± 0.38	0.94 ± 0.42
Lateral hamstrings	0.93 ± 0.08	0.91 ± 0.13	0.93 ± 0.12
Gluteus medius	0.95 ± 0.08	0.96 ± 0.10	0.98 ± 0.10

LPV = Linear phase-varying model; NPV = Nonlinear phase-varying model; PV = Phase-varying model; RRV = Relative remaining variance

† Significant difference in prediction accuracy between the PV and LPV models

‡ Significant difference in prediction accuracy between the PV and NPV models

Predictions of myoelectric responses were poor (RRV ≈ 1.00) across muscles at all except the shortest prediction window (θ = 6.3%). At the shortest prediction window, both the LPV and NPV models' predictions for the hamstrings, rectus femoris, and gastrocnemius were 10.7–15.0% more accurate than those of the PV model ($p < 0.001$; Fig. 4). However, even at a prediction window of θ = 12.5% of a stride, the LPV model's average prediction accuracies were not different from those of the PV model ($p > 0.050$). Across all muscles, the LPV and NPV models exhibited similar average prediction accuracies ($p > 0.009$).

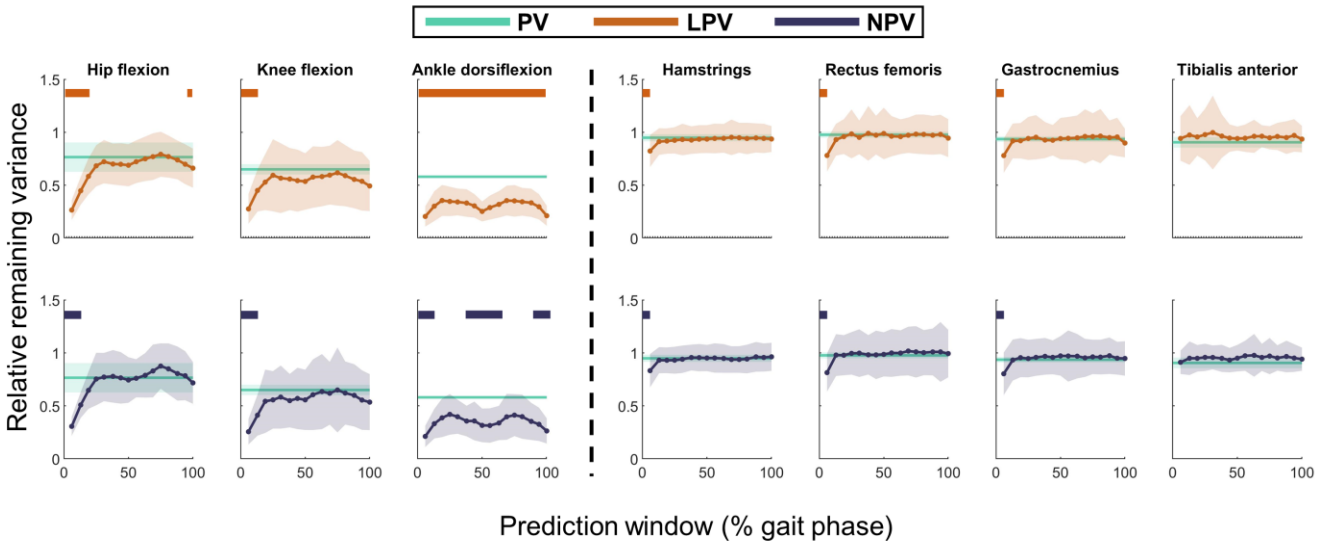

Fig. 4. Prediction accuracy decreased with increasing prediction window length. The PV model's predictions (green) were constant across prediction windows. Horizontal bars denote predictions that were significantly more accurate than the PV model. The LPV (top; orange) and NPV (bottom; purple) models' prediction accuracies approached nearly constant values for predictions beyond 25.0% of a stride for kinematic responses and 6.3% of a stride for myoelectric responses. However, the LPV and NPV models' predictions of ankle kinematics, which were directly correlated with exoskeleton torque, remained more accurate than PV model predictions for all prediction windows, while knee and hip kinematic predictions were similar to those of the PV model beyond 25.0% of a stride. All myoelectric prediction accuracies approached those of the PV model as the prediction window increased.

The LPV and NPV models' prediction accuracies improved with increasing training set size set for all outputs. As expected, the PV model's prediction accuracy was nearly constant across training set sizes ($p > 0.038$; Fig. 5). For a prediction window of θ = 12.5% of a stride, the LPV model's prediction accuracies at the hip were significantly worse than RRV_{full} only when using approximately 25 strides of training data per exoskeleton condition (RRV = 0.81; $p < 0.001$), while knee and ankle predictions were not significantly worse than RRV_{full}, even with only 25 training strides per condition. The NPV model's hip, knee, and ankle prediction accuracies were worse than RRV_{full} only when models were trained using 25 training strides per

condition ($p < 0.001$). Compared to training the LPV and NPV models with 25 strides of data per condition, training with 50 strides of data resulted in average improvements in prediction accuracies of 0.32, 0.32, and 0.16 RRV points at the hip, knee, and ankle, respectively. Beyond approximately 125 strides of training data per condition, kinematic prediction accuracies improved by less than 0.01 RRV points per 25 training strides. Myoelectric prediction accuracies were statistically worse than RRV_{full} only with 25 strides of training data per condition in the hamstrings and gastrocnemius for the LPV model, and the tibialis anterior for the NPV model ($p < 0.001$). The LPV and NPV models' prediction accuracies were qualitatively similar across training set sizes (Fig. 5).

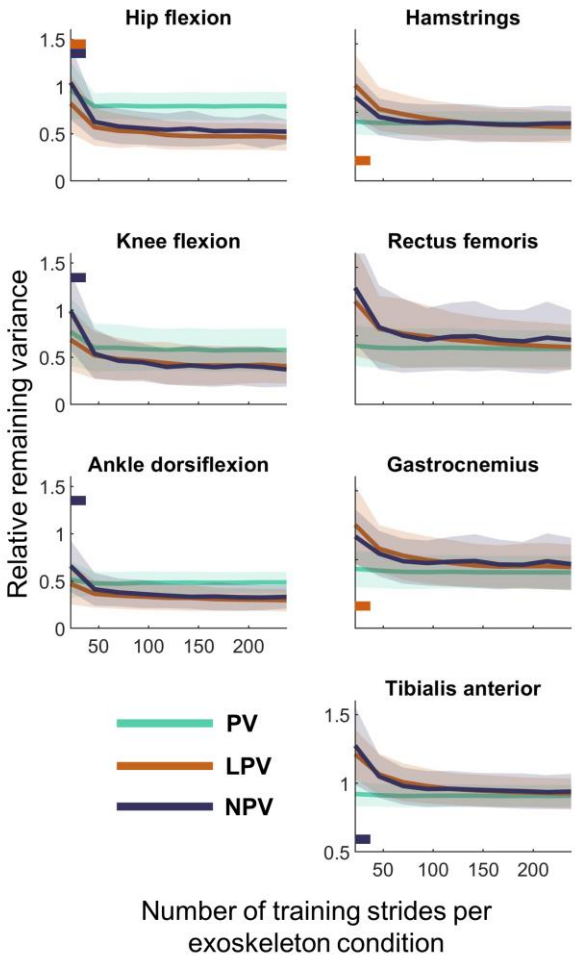

Fig. 5. Average (±1SD; shaded region) prediction accuracy of kinematic (left) and myoelectric (right) outputs for the PV (green), LPV (orange), and NPV (purple) models over training set sizes ranging from 24 to 240 cycles per exoskeleton condition. Prediction accuracies were reported at a θ = 12.5% stride prediction window. Orange (LPV) and purple (NPV) horizontal bars denote the training set sizes that yielded significantly worse predictions than those of the full training set. The PV model's prediction accuracies were not significantly different from RRV_{full} at any training set size.

VI. Discussion

We evaluated the ability of phase-varying models to predict kinematic and myoelectric responses to ankle exoskeleton torques during treadmill walking. Linear and nonlinear models predicted kinematic responses to exoskeletons without knowledge of the specific user's physiological characteristics, supporting their potential utility as predictive tools for exoskeleton design and control. To our knowledge, this is the first study to predict kinematic and myoelectric responses to ankle exoskeletons using phase-varying models. Consistent with Floquet Theory and prior models of human locomotion, LPV models appear appropriate for predicting responses to exoskeleton torque over short prediction windows, evidenced by its similar prediction accuracy to the more complex NPV model and improved prediction accuracy over the less complex PV model [25-27, 29].

The small and variable responses to exoskeleton torque exhibited by the unimpaired adults in this work highlight the challenge of altering kinematics with passive ankle exoskeletons. We found that even stiff exoskeletons (K = 5.08 Nm/deg) only altered ankle kinematics on average by six degrees and integrated muscle activity by 13.8%. These small changes indicate that the present study is a rigorous test case. Even small changes in kinematics or muscle activity may contribute to large changes in joint powers or metabolic demands during walking, making the predictions of individualized responses essential for applications that seek to improve gait through subject-specific exoskeletons design [1, 2, 6, 16].

Our hypothesis that the LPV model would predict kinematic and myoelectric responses more accurately than the PV model and as accurately as the NPV model was partially supported. The LPV model's kinematic and myoelectric predictions were more accurate than those of the PV model only for prediction windows less than 18.8% and 6.3% of a stride, respectively, while the LPV and NPV models exhibited similar prediction accuracies across prediction windows. The LPV and NPV models' similar predictions support prior research demonstrating that nonlinear spring-loaded inverted pendula (SLIPs) have similar predictive accuracy to

linear models of human movement [25]. Compared to the nonlinear SLIP, the NPV model's feedforward neural network imposed fewer restrictions on model structure. Therefore, the differences in prediction accuracy between the LPV and NPV models should be at least as large as those observed between the linear models and physics-based nonlinear models like the SLIP in [25]. Consistent with applications of Floquet Theory for rhythmic locomotion at a constant speed over level ground, linear phase-varying models appear to have sufficiently complex structure to predict kinematic responses to exoskeletons [25-27, 29].

We observed comparable kinematic prediction accuracy to studies using physics-based and data-driven models of locomotion. Maus et al. evaluated multiple models' abilities to predict center-of-mass height during running and reported accuracies ranging from RRV ≈ 0.15 at a 15% prediction window to RRV ≈ 0.85 beyond an 80% stride prediction window, for an exemplary participant [25]. Within a similar range of prediction windows, the LPV model predicted kinematics across participants with average accuracies ranging from ($0.30 < RRV < 0.45$) at a 12.5% prediction window and ($0.34 < RRV < 0.77$) at an 81.3% prediction window. Similarly, Drnach et al. [43] used a hybrid linear model to predict response to functional electrical stimulation, reporting median RRV values (transformed from a fitness score) ranging from approximately 0.11-1.04. However, the average unperturbed gait cycle was not subtracted from the data before computing the fitness score in [43]. The average unperturbed cycle accounts for a substantial portion of the variance in the perturbed signals, providing a less conservative prediction accuracy statistic than the RRV presented here. For example, in the present study, the unperturbed (K_0) gait cycle accounted for approximately 65% of the variance in ankle kinematics of the validation data (K_2) for a participant who exhibited a large response to torque. If the unperturbed cycle had not been subtracted from the data, this participant's prediction accuracy for the LPV model would equal 0.08 rather than the more conservative 0.21 reported. Comparable prediction accuracies to prior work indicate that phase-varying models represent useful predictive tools for locomotion with ankle exoskeletons and may have similar predictive power to physics-based models of locomotion.

The convergence of LPV and NPV models' prediction accuracies to an approximately constant value at large prediction windows (e.g. $RRV_{LPV} \approx 0.70$ for knee kinematics at $\theta > 25.0\%$ of a stride) may inform measurement selection for device design. The LPV and NPV models' kinematic prediction accuracies decreased rapidly from 6.3% to 18.8% stride prediction windows, before reaching an approximately constant value. Ankle predictions remained better than those of the PV model across prediction windows due to the direct relationship between exoskeleton torque and ankle angle. The torque-ankle angle relationship of passive exoskeletons implies that a perfect estimate of exoskeleton torque would yield a nearly perfect prediction of ankle kinematics (RRV $\approx$ 0). However, we assumed a simplified torque-ankle angle relationship, while deformation of soft tissue and the exoskeleton introduces some uncertainty into exoskeleton torque profile estimates, resulting in good, but not perfect predictions of response (RRV > 0.20) [44]. Conversely, hip and knee kinematics were indirectly impacted by exoskeleton torque, and their RRV values approached those of the PV model for prediction windows above 18.8% of a stride. Only for short prediction windows ($\theta \leq 18.8\%$ of a stride) were stride-specific initial posture and exoskeleton torque predictive of future hip and knee kinematics. At large prediction windows, measurements at an initial phase did not, on average, improve predictions of future posture due to a loss of coherence between inputs at an initial phase and outputs at a final phase [41]. However, some participants' hip and knee kinematics were predicted more accurately – by up to 0.30 RRV points – by the LPV and NPV models than the PV model across large prediction windows, suggesting that the prediction window length at which stride-specific measurements no longer improve predictions of response exoskeleton torque depends on the magnitude of the individual's response to torque. Guided adaptation and extended practice sessions [1, 18] or powered ankle exoskeletons [5-7] may elicit larger responses than those observed in this study and increase the maximum prediction windows at which measurements at an initial posture may improve predicted responses to torque and inform device design.

A major limitation of all three models was their inability to predict myoelectric responses. Despite qualitatively good average predictions, the LPV and NPV models predicted myoelectric signals more accurately than the PV model only for the shortest prediction window. While prior work suggests that exoskeleton torque and stiffness impact average soleus and gastrocnemius activity, the cycle-to-cycle variability in myoelectric responses in our data was large compared to the average response [1, 10, 12]. We found that the average unperturbed gait cycle accounted for 30-60% of the variance in the K_2 data, compared to 60-95% in kinematic signals. Consequently, poor prediction accuracy may be partially attributed to small changes in observed muscle activity between the exoskeleton conditions. However, the myoelectric and kinematic input variables used as model inputs may also be insufficient to encode nonlinear musculotendon dynamics between the initial and final phases, which are impacted by ankle exoskeletons [17, 40, 45]. Studies that quantified myoelectric prediction accuracy using physiologically-detailed musculoskeletal models accounted for 60-99% of the variance in myoelectric signals, though they did not remove the average cycle prediction and reported prediction accuracies for unperturbed walking conditions only [46, 47]. Still, the differences in prediction accuracies between the phase-varying models presented here and musculoskeletal models indicates that using shorter prediction windows or including physiological detail in the input variables to encode musculotendon dynamics are likely needed to improve myoelectric predictions for data-driven phase-varying models and represent interesting areas of future research.

An additional limitation of data-driven phase-varying models, compared to physiologically-detailed models, is the amount of training data required to reliably estimate model parameters and predict changes in gait with exoskeletons. The required training set size will impact the utility of phase-varying models in real-world settings, such as clinical gait laboratories, where minimizing data collection duration is critical to mitigating physical and logistical burdens on participants and families. The LPV and NPV models required similar amounts of training data – 50 strides per exoskeleton condition – for prediction accuracies to approach those of predictions using the full training set, though accuracies continued to improve at a slower rate. The sharp

improvement in prediction accuracy between 25 and 50 strides of training data per condition suggests that at least 50 strides of training data per experimental condition should be collected when predicting unimpaired kinematic responses to exoskeletons using phase-varying models. However, collecting up to 125 training strides per condition may further improve prediction accuracy. For individuals walking at approximately one stride per second, using 50 training strides per condition is similar to the amount of training data used by Drnach et al., who trained a hybrid linear model using 45 seconds of data across two experimental conditions and reported comparable kinematic prediction accuracies [43]. For unimpaired, rhythmic locomotion, predicting kinematic responses to ankle exoskeletons using phase-varying models appears to require 50–125 strides of training data per condition, supporting their feasibility only in gait analysis settings with treadmills or long walkways. When only a single experimental condition or a small number of strides are collected, as is standard in clinical gait analysis, physiologically-detailed models will likely generate more accurate predictions than phase-varying models [46, 47, 50]. However, using dimensionality reduction techniques, such as factor analysis or sparse regression for LPV models, may reduce the amount of training data required [25, 31, 49].

The utility of data-driven phase-varying models for human locomotion with exoskeletons is application- and resource-dependent. While we investigated only a specific subset of phase-varying models, we showed that this class of model can predict kinematic responses to exoskeletons without knowledge of an individual's physiology. Moreover, unlike physiologically-detail models, this work and prior studies exemplify phase-varying models' ability to take arbitrary measurements as inputs, such as joint angles and muscle excitations used in this study, limb segment orientations, or marker trajectories, enabling their application across studies with different experimental resources and exoskeletal or prosthetic devices [25, 26, 31]. However, poor myoelectric prediction accuracy limits the utility of the specific phase-varying models investigated in this work for predicting neuromuscular responses to exoskeletons. Future investigation to improve data-driven predictions of myoelectric responses to exoskeletons, in combination with analytical tools for phase-varying

systems, such as Data-Driven Floquet Analysis [31], may facilitate prediction and analysis of individualized exoskeleton impacts on gait mechanics and motor control across different experimental settings.

VII. Conclusion

To our knowledge, this is the first study to predict subject-specific responses to ankle exoskeletons using phase-varying models. Without making assumptions about individual physiology or motor control, an LPV model predicted short-time kinematic responses to bilateral passive ankle exoskeletons, though predicting myoelectric responses remains challenging. Results support the utility of LPV models for studying and predicting response to exoskeleton torque. Improving data-driven models and experimental protocols to study and predict myoelectric responses to exoskeletons represents an important direction for future research. Modeling responses to exoskeletons or other assistive devices using a phase-varying perspective has the potential to inform exoskeleton and prosthesis design for a range of user groups.

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