A Data-Driven Predictive Model of Individual-Specific Effects of FES on Human Gait Dynamics*

Luke Drnach, *Student Member, IEEE*, Jessica L. Allen, Irfan Essa, and Lena H. Ting, *Member, IEEE*

***Abstract*— Modeling individual-specific gait dynamics based on kinematic data could aid development of gait rehabilitation robotics by enabling robots to predict the user's gait kinematics with and without external inputs, such as mechanical or electrical perturbations. Here we address a current limitation of data-driven gait models, which do not yet predict human responses to perturbations. We used Switched Linear Dynamical Systems (SLDS) to model joint angle kinematic data from healthy individuals walking on a treadmill during normal gait and during gait perturbed by functional electrical stimulation (FES) to the ankle muscles. Our SLDS models were able to predict the time-evolution of joint kinematics in each of four gait phases, as well as across an entire gait cycle. Because the SLDS dynamics matrices encoded significant coupling across joints, we compared the SLDS predictions to that of a kinematic model, where the joint angles were independent. Gait kinematics predicted by SLDS and kinematic models were similar over time horizons of a few milliseconds, but SLDS models provided better predictions of gait kinematics over time horizons of up to a second. We also demonstrated that SLDS models can infer and predict individual-specific responses to FES during swing phase. As such, SLDS models may be a promising approach for online estimation and control of and human gait dynamics, allowing robotic control strategies to be tailored to an individual's specific gait coordination patterns.**

I. Introduction

Gait rehabilitation robotics, particularly exoskeletons, have used reference trajectories to guide joint angles of the lower limbs [1]. Reference trajectories are typically obtained by averaging the gait patterns of multiple healthy individuals together, or by recording the gait of a user, either healthy or impaired, beforehand. In the case of impaired gait, the reference can be taken from the unimpaired leg and mirrored to form a complete specification for both legs, under the assumption that joint kinematics can be independently specified. Robot controllers then attempt to follow each joint trajectory in the reference independently, either through position or impedance control.

Recent work using model-predictive control of exoskeletons based on reference trajectories have shown that controller performance suffers when human gait dynamics are not taken into account [2]. Controlling around a reference trajectories assumes that the human behaves passively; as a result, human limb dynamics and interjoint coupling are treated as disturbances that cannot be completely rejected. However, human joints are not independently controlled either within or between limbs [3,4,5], and interjoint coupling can be even more pronounced in impaired populations [6]. Further, in the case of asymmetric impairments, the dynamics of the impaired leg also affects the coordination of the less impaired leg, allowing compensation via mechanical and/or neural coupling [4]. Estimating predictive models of human limb dynamics online could substantially improve human-robot interactions in gait. Improved models should predict the limb kinematics based on joint coupling, as in [7], but also predict the individual's response to dynamic interactions with the robot. Explicitly modeling dynamic human-robot interactions could help the robot predict how changing joint torques affects all of the joints through the individual's coordination dynamics, allowing robot controllers to be tailored to individual-specific behaviors and responses [8].

Switched linear dynamical systems (SLDS) have been used in the machine learning community for recognizing different gaits, and may be a useful model for predicting human gait. SLDS model nonlinear behavior, such as gait, as a piecewise linear system; each of the linear systems governs only a part of the overall system, and a set of discrete modes determine which linear system is active. The linear system parameters of an SLDS can either be specified from physical knowledge, as in [9], or estimated from data, as in [10-14]. Each linear system of an SLDS can be designed to represent different gaits, such as running, walking, and limping [10,11], or to represent other whole-body behaviors like sit-to-stand [12]. Previously, we demonstrated that individual autonomous linear systems in a SLDS model can identify single and double-limb support gait phases [13].

While SLDS models are typically used to recognize different gait behaviors, they can also generate gait patterns that are qualitatively similar to human gait [14]. Because each part of an SLDS is linear, the behavior of the original system can be quickly predicted using linear forecasting techniques. However, the performance of SLDS in predicting human gaits has yet to be quantitatively measured. SLDS models to date also have not included control terms to model the effects on gait of mechanical forces and torques from an exoskeleton or electrical stimulation to the muscles.

Our goal was to demonstrate that an SLDS model of gait, trained on an individual's specific gait kinematics in both unperturbed and in perturbed walking, can reproduce

*This material is based upon work supported by the National Science Foundation under Grant Nos. DGE-1545287, M3X-1762211, and DGE-1650044. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do no necessarily reflect the views of the National Science Foundation.

L. Drnach and I. Essa are with Georgia Institute of Technology, Atlanta, GA, 30332 USA.

J.L. Allen is with West Virginia University, Morgantown, WV, 26506 USA.

L.H. Ting is with Georgia Institute of Technology and Emory University, Atlanta, GA, 30322 USA, and is the corresponding author. (email: lting@emory.edu)

the individual's normal walking pattern and their unique response to a perturbation. Here, we focused on evaluating the dynamics of each phase-specific linear system in an SLDS; specifically, we hypothesized that each of our linear systems could predict joint angle trajectories for the corresponding gait phase by including information about interjoint coordination. We compared simulated gait trajectories to the measured trajectories in each phase for unperturbed gait. Then, we compared simulations with and without simulated inputs to the perturbed gait to assess the model's ability to predict individual responses to gait perturbations. We also compared the SLDS model's performance to a simple kinematic model based on independent joint trajectories. Our results show that, while the SLDS behaves locally like a kinematic model, SLDS can also predict both unperturbed gait kinematics and individual responses to perturbations in different gait phases, and across an entire gait cycle.

II. Methods

A. Gait Data

Data was collected from five healthy participants (all female, 24-25 years old) while walking at constant speed on a split-belt treadmill instrumented with force platforms embedded within each belt. All participants provided written informed consent prior to participating according to protocols approved by the institutional review boards at both Emory University and Georgia Institute of Technology. Three-dimensional kinematics from both legs were captured at 100Hz using a seven-camera motion capture system and the Vicon Plug-In Gait model. Ground reaction forces (GRFs) were recorded at 1000Hz. Vertical GRFs were used to identify gait events using a 50N threshold. Specifically, we defined heel-strikes as when the force first exceeds 50N and toe-offs as when the force first drops below 50N.

Subjects were given 3-5 minutes to acclimate to treadmill walking. Afterwards, each subject walked at two conditions for 45s each at matched walking speeds in the following order: (1) baseline walking and (2) perturbed walking. In the perturbed walking condition, functional electrical stimulation (FES) was delivered to the right ankle dorsiflexor muscles during the right swing phase and the right plantarflexors during right terminal double support phase. Two footswitches were attached under the sole of the shoe of the right leg to determine gait events for closed-loop control of FES [15].

B. Gait as a Switching Linear Dynamical System

We modeled the joint kinematics of the lower legs during gait as a switching linear dynamical system. An SLDS is of a set of linear dynamical systems with discrete modes that govern when to switch between the individual linear models. The equation for an SLDS in discrete-time can be written as:

$$x_{k+1} = A_{z_k} x_k + B_{z_k} u_k + w_k(z_k) \tag{1}$$

where z_k is the discrete mode index at time k, $z_k \in \{1, , N\}$, x_k the observed state at time k, A_{z_k} and B_{z_k} are the linear system parameters associated with the discrete mode z_k, and $w_k(z_k)$ is a zero-mean, Gaussian noise term whose covariance matrix Σ_{z_k} is also associated with the discrete mode z_k. The probability of starting in each discrete mode is given by the initial state distribution, π , and transitioning between hidden states is governed by a transition probability:

$$p(z_{k+1} = j | z_k = i) = T_{ij} \tag{2}$$

The model parameters $\Theta = (A, B, \Sigma, T, \pi)$ were estimated from data $X = (x_1, u_1), (x_2, u_2), , (x_K, u_K)$ following a variant of the Baum-Welch algorithm for Hidden Markov Models [16]. In the expectation step, we calculated the probability of being in discrete mode i at time k:

$$\gamma_k(i) = p(z_k = i | X, \Theta) \tag{3}$$

and the probability of transitioning from discrete mode i to discrete mode j:

$$\xi_k(i, j) = p(z_k = i, z_{k+1} = j | X, \Theta) \qquad (4),$$

where both probabilities are estimated using the forwards-backwards algorithm [13]. In the maximization step, we updated the model parameters according to:

$$\pi_i = \gamma_1(i) \tag{5}$$

$$a_{ij} = (\sum_{k=1}^{K-1} \xi_k(i, j)) / (\sum_{k=1}^{K-1} \gamma_k(i)) \tag{6}$$

$$[A_i, B_i] = [\sum_{k=1}^{K} \gamma_k(i) x_k \hat{x}_{k-1}^\top][\sum_{k=1}^{K} \gamma_k(i) \hat{x}_{k-1} \hat{x}_{k-1}^\top + \lambda I]^{-1} \tag{7}$$

$$\Sigma_i = (\sum_{k=1}^{K} \gamma_k(i) w_k(i) w_k^\top(i)) / (\sum_{k=1}^{K} \gamma_k(i)) \tag{8}$$

where $w_k(i) = x_{k+1} - A_i x_k - B_i u_k$ and $\hat{x}_k = [x_k^\top, u_k^\top]^\top$. Given a set of initial parameters, we iterated between expectation and maximization steps until the absolute difference in log-likelihood between consecutive iterations was less than a pre-defined threshold. To initialize the models, we used a procedure previously described to estimate gait phases based on kinematic features [13]. In brief, we initialized heel strikes from the time of the minimum in knee flexion over a gait cycle, and toe-offs as the time of the minimum in ankle flexion. We then initialized each LDS model in the SLDS based on the kinematically determined gait events.

Here, we have introduced a regularization term λ into the estimation of the linear system parameters $[A_i, B_i]$ that was not present in our previous work [13]. This term is analogous to a penalty on the regression coefficients $[A, B]$ in a linear regression cost function and serves to drive unnecessary elements in the dynamics towards zero. With the addition of the regularization term, we are no longer guaranteed a monotonic increase in likelihood by iterating between expectation and maximization, as is guaranteed by the traditional Baum-Welch algorithm. However, our models converged even with nonzero regularization values.

To model individual-specific gait dynamics, we trained a four-state SLDS on each individual's gait data in both constant speed walking and walking with FES perturbations.

We formulated a second-order model using generalized coordinates for our state vector, $x_k = [\theta_k, \theta_{k-1}]$, where k is a vector of measured joint angles at time k. We included hip flexion and adduction, knee flexion, and ankle flexion and adduction angles of both left and right legs in our model. We also modeled the perturbation as an input square wave with magnitude 1 from left heel strike to right heel strike, and 0 otherwise - i.e. the input is on in double support phase with left leg forward and right leg swing phase. Transitions between discrete modes were constrained to form a cycle, with only one mode following after another.

We trained the models on a bout of constant speed walking (no input) and a bout of walking with FES perturbation (square wave input). To set the regularization parameter, we trained on the first 75% of the data in each bout, and then validated the model on the remaining 25%. We tested 10 values of the regularization parameter, logarithmically spaced between 0.1 and 100. For each individual, we chose the value of λ that minimized the average normed error, $1/K \sum_k \|w_k\|$, on the validation data.

We also trained a single SLDS on constant speed walking and walking with FES perturbation from all five participants, using the same cross-validation procedure described for each of the individual-specific models. The group SLDS model was trained on the first 75% of each individual's walking data in both conditions; the remaining 25% from each participant in each condition was used to select the regularization parameter based on the minimizing the average normed error.

C. Verifying SLDS modes are gait phases

Using the gait events obtained from the force platforms, we constructed a ground-truth gait phase sequence to validate that the SLDS discrete modes correspond to gait phase dynamics. We defined left swing phase from left toe-off until left heel-strike, left double support phase from left heel-strike to right toe-off, right swing phase from right toe-off to right heel-strike, and right double support phase from right heel-strike to left toe-off. We labeled each point in the joint angle trajectories with its corresponding gait phase.

We used the Viterbi Algorithm [17] to infer the gait phases associated with the kinematics, based on the SLDS model. Using both the model-predicted gait phases and the gait phases determined by force plates, we calculated the accuracy as the fraction of all labeled phases that matched the phases determined by the ground reaction forces. We calculated the confusion matrix, recall, precision, and accuracy for each participant using their individual-specific SLDS model, and calculated the mean and standard deviation across participants. We repeated this procedure with the SLDS model trained on data from all participants, and compared the results to those obtained from individual-specific model.

D. Comparing SLDS locally to a kinematic model of gait

To demonstrate the importance of joint coupling in gait dynamics, we compared the SLDS model to a velocity-based kinematic model of the form:

$$x(t + dt) = x(t) + v(t)dt \tag{12}$$

We implemented this as a second-order discrete-time model:

$$x_{k+1} = 2x_k - x_{k-1} \tag{13}$$

comparable to the second-order models in our SLDS.

For individual-specific SLDS, the group SLDS, and kinematic models, we calculated the local fitness of each model for each joint angle as:

$$fit_j = 1 - \sqrt{\sum_{k=1}^{K} (\theta_k(j) - \hat{\theta}_k(j))^2 / \sum_{k=1}^{K} (\theta_k(j) - \bar{\theta}(j))^2} \tag{14}$$

where $\theta(j)$ is the $j^t h$ measured joint angle, $\hat{\theta}_k(j)$ is the value of the $j^t h$ joint angle predicted from the previous measured values, $\theta_{k-1}(j)$ and $\theta_{k-2}(j)$, and $\bar{\theta}(j)$ is the average value of $\theta(j)$. A fitness score of 1 indicates a perfect fit, while scores less than 0 indicate the model performs worse than the mean. We calculated the fitness score on both gait with no FES (no inputs) and with FES (with square wave inputs).

E. Using SLDS to generate gait kinematics

We compared the kinematic and SLDS models' ability to simulate gait kinematics from initial conditions. For each gait cycle in the training data, we simulated the kinematics in each gait phase from the first two joint angles in that phase using both the kinematic model and the SLDS. For simulations with the SLDS, we simulated the kinematics of each phase using only the linear models corresponding to the given phase. For each model, we quantified the simulation quality using a fitness score similar to Eq (14), except we used $\hat{\theta}_k(j)$ as the generated trajectory over multiple time steps instead of over one time step. As before, a fitness of 1 indicates the model perfectly simulates the gait trajectory, while a fitness less than 0 indicates the simulation is worse than using the mean. We repeated the simulation with both the individual-specific and the group SLDS models.

Finally, we also used the SLDS to predict entire gait cycles, given only the initial conditions and the measured gait phases; we gave the SLDS the measured gait phases to avoid errors arising from stochastically switching between linear models in the SLDS. We simulated multiple gait cycles in walking with and without FES, where the input term u was provided during walking with FES simulations. All simulations started at the left toe-off gait event, as measured by the force plates, and initial conditions were the current and previous joint angle measurements at the gait event. We computed the average fitness for each joint angle across multiple simulated gait cycles for each individual, using both the individual-specific and the group SLDS models.

III. Results

A. SLDS identifies gait phases from joint kinematics

The discrete modes of the individual-specific SLDS corresponded to measured gait phases with $84 \pm 11\%$ and $82 \pm 9\%$ average accuracy across individuals in walking without and with FES, respectively. Precision and recall scores for the indivdiual-specific models are listed in Table 1. In contrast, the discrete modes of the group SLDS corresponded to measured gait phases with $42 \pm 3\%$ and $39 \pm 4\%$ average accuracy in walking without and with FES, respectively.

B. SLDS dynamics matrices encode joint coupling

Comparing individual-specific SLDS dynamics to a kinematic model with independent joints qualitatively suggested that the SLDS model approximated a kinematic model but with interjoint coupling (Figure 1). Inter-joint coupling elements withing gait phases were the most variable across individuals, with different couplings exhibiting the most variance across individuals in different gait phases (Maximum Variance Element in (a) left swing: left hip flexion to left ankle flexion, $\sigma^2 = 1.94$; (b) left double support: right ankle adduction to left knee flexion, $\sigma^2 = 1.19$; (c) right swing: left ankle flexion to right ankle flexion, $\sigma^2 = 0.31$; (d) right double support: left ankle adduction to right knee flexion, $\sigma^2 = 0.92$). However, across individuals and gait phases, the SLDS dynamics matrices shared a common structure: all joint angles appeared strongly coupled to their own history, and many were coupled to the histories of other joints.

C. SLDS is locally similar to a kinematic model

Across individuals, the individual-specific SLDS model's one-step predictions accounted for 93-99% of the deviations in joint angle trajectories from their mean values for walking without FES. Likewise, the kinematic models also accounted for 89-98% of the deviation in joint angles, and the group SLDS model accounted for 92-99% of the deviation. We found no statistically significant difference in local fitness among the kinematic, individual-specific, and group SLDS models in any of the joint angles (Kruskal-Wallis one-way analysis of variance, medians and interquartiles ranges in Table II, 14 DoF, $\chi^2 < 74$, $p > 0.005$ for all joint angles, Bonferroni corrected for multiple comparisons). We found similar results on walking with FES.

TABLE I

CONFUSION MATRICES FOR INFERRED GAIT PHASES

Unperturbed Gait

	Force Plate Measured Phases			
	L.Swing	L.Support	R.Swing	R.Support
L.Swing	$28 \pm 3\%$	$0 \pm 0\%$	$0 \pm 0\%$	$1 \pm 1\%$
L.Support	$5 \pm 1\%$	$16 \pm 2\%$	$1 \pm 1\%$	$0 \pm 0\%$
R.Swing	$0 \pm 0\%$	$1 \pm 1\%$	$26 \pm 11\%$	$1 \pm 2\%$
R.Support	$1 \pm 1\%$	$0 \pm 0\%$	$7 \pm 12\%$	$14 \pm 1\%$
Recall	$81 \pm 6\%$	$97 \pm 4\%$	$77 \pm 33\%$	$90 \pm 13\%$
Precision	$97 \pm 4\%$	$73 \pm 4\%$	$93 \pm 9\%$	$74 \pm 24\%$

Perturbed Gait

	Force Plate Measured Phases			
	L.Swing	L.Support	R.Swing	R.Support
L.Swing	$27 \pm 4\%$	$0 \pm 0\%$	$0 \pm 0\%$	$1 \pm 2\%$
L.Support	$6 \pm 2\%$	$14 \pm 1\%$	$2 \pm 1\%$	$0 \pm 0\%$
R.Swing	$0 \pm 0\%$	$0 \pm 1\%$	$26 \pm 9\%$	$1 \pm 2\%$
R.Support	$1 \pm 1\%$	$0 \pm 0\%$	$7 \pm 10\%$	$15 \pm 2\%$
Recall	$81 \pm 7\%$	$97 \pm 6\%$	$75 \pm 26\%$	$90 \pm 16\%$
Precision	$96 \pm 5\%$	$67 \pm 9\%$	$94 \pm 8\%$	$73 \pm 24\%$

D. SLDS can generate individual responses to perturbations

Using kinematic, individual-specific SLDS, and group SLDS models to generate joint angle trajectories in each gait phase, we found SLDS generated trajectories were qualitatively similar to the trajectories in the training data, while trajectories generated by the kinematic model followed straight lines and quickly diverged from the measured trajectories (Figure 2). Median fitness values for the kinematic model were less than 0 for all joint angles except left and right hip flexion in both perturbed and unperturbed walking. In contrast, median fitness values for the SLDS generated trajectories were greater than 0 across simulation conditions. Kruskal-Wallis analysis of variance indicated that fitness scores from kinematic, individual-specific, and group SLDS models were significantly different (medians in Figure 2, $\chi^2 > 100$, 14 DoF, $p < 0.005$, corrected for multiple comparisons) for all joint angles except left knee flexion,

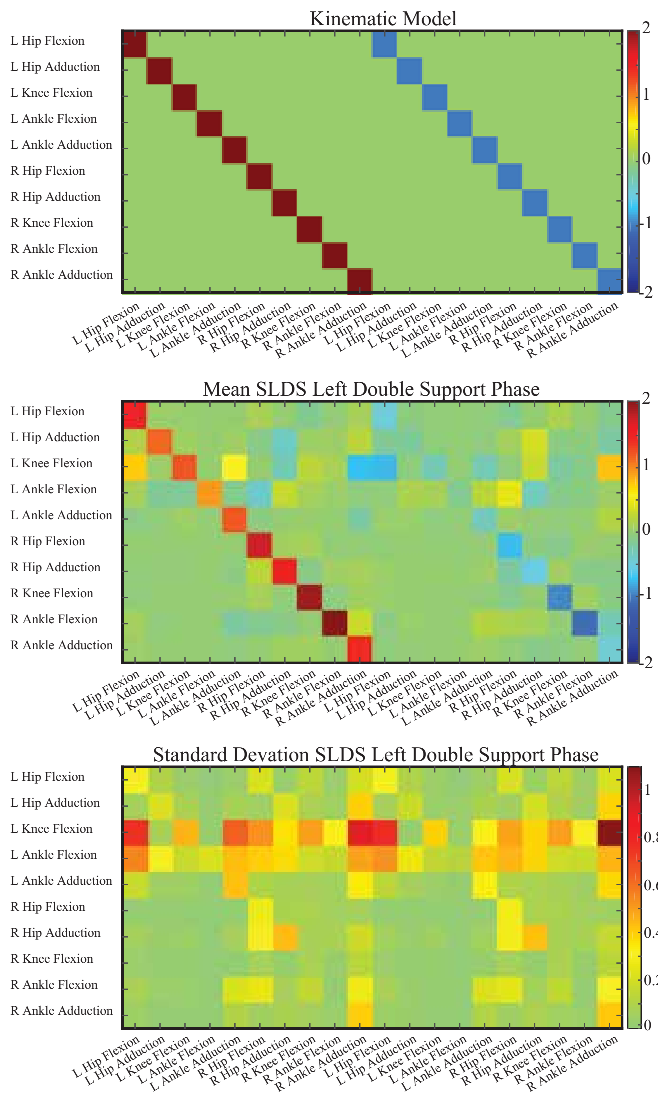

Fig. 1. Mean and standard deviation of the individual-specific SLDS left double support dynamics, compared to a kinematic model. SLDS models contain substantial off-diagonal terms, which indicate joint coupling.

TABLE II

KINEMATIC AND SLDS LOCAL FITNESS ON UNPERTURBED GAIT

		SLDS	
Joint Angle	Kinematic	Individual	Group
L. Hip Flexion	0.98 ± 0.00	0.99 ± 0.00	0.99 ± 0.00
L. Hip Adduction	0.93 ± 0.02	0.95 ± 0.01	0.95 ± 0.01
L. Knee Flexion	0.98 ± 0.03	0.99 ± 0.02	0.98 ± 0.01
L. Ankle Flexion	0.94 ± 0.06	0.96 ± 0.04	0.95 ± 0.04
L. Ankle Adduction	0.90 ± 0.03	0.93 ± 0.03	0.92 ± 0.02
R. Hip Flexion	0.99 ± 0.01	0.99 ± 0.01	0.99 ± 0.01
R. Hip Adduction	0.92 ± 0.03	0.95 ± 0.02	0.94 ± 0.01
R. Knee Flexion	0.98 ± 0.03	0.99 ± 0.01	0.99 ± 0.01
R. Ankle Flexion	0.89 ± 0.04	0.93 ± 0.03	0.92 ± 0.02
R. Ankle Adduction	0.95 ± 0.01	0.96 ± 0.01	0.95 ± 0.00

which approached significance ($\chi^2 = 105$, DoF = 14, p = 0.0052). A subsequent one-tailed Wilcoxon Rank-Sum test revealed that both the individual-specific and group SLDS fitness values were statistically greater than those for the kinematic model (medians in Figure 2, RankSum = 15, $p < 0.005$ for all comparisons) for all joint angles. Fitness of the individual-specific models was also statistically greater than that of the group model for left ankle flexion, left ankle adduction, right hip flexion, and right ankle flexion (one-tailed Rank-Sum test, RankSum = 40, $p < 0.005$), and approached significance for all other angles (one-tailed Rank-Sum Test, RankSum$>$ 34, $p < 0.08$). All medians were calculated within a joint angle, but across individuals.

SLDS models without input terms predicted gait kinematics in walking without FES well, but underestimated gait kinematics for walking with FES in right swing phase (Figure 2). Across individuals, the SLDS models improved their prediction of right swing kinematics when the input was provided to model the FES perturbation. Modeling the input as a squarewave improved the individual-specific model's generated right ankle flexion trajectory (one tailed Wilcoxon Rank-Sum Test, without input median fitness = 0.57, with input median fitness = 0.71, RankSum = 15, $p < 0.005$). Model fitness with the group SLDS was not statistically greater with the input for any of the joint angles. Overall, the individual-specific models had statistically greater median fitness values for simulated gait with FES perturbations for all joints (one tailed Rank Sum Test, medians in Figure 2, RankSum = 40, $p < 0.005$) except Left Knee Flexion, which approached significance (RankSum = 37, $p = 0.027$).

E. SLDS can generate trajectories for an entire gait cycle

Starting from left swing phase, individual-specific SLDS models generated gait kinematics that were similar to the kinematics in the training data for both walking without and with FES when the input was provided to model the FES perturbation (Figure 3). Median fitness scores across individuals for individual-specific models ranged from -0.02 for left ankle adduction to 0.79 for left hip flexion for both FES conditions. We found no statistically significant difference in median fitness between indivdiual-specific simulations and group SLDS simulations of walking without FES, although several joints approached significance (one-tailed Rank Sum Test, medians in Figure 3, $35 <$ RankSum < 39, $p < 0.05$). Likewise, only the fitness for Left Hip Flexion was significantly greater for individual-specific models compared to group models (Rank-Sum Tesst, RankSum = 40, $p < 0.005$), while several other joint angles approached significance.

IV. DISCUSSION

Our work demonstrating that SLDS can generate gait trajectories is an important step towards developing data-driven gait models for use in rehabilitation robotics. One advantage of our SLDS approach over a reference trajectory or a statistical model of joint kinematics is that the SLDS can predict changes in gait resulting from a perturbation, such as the mechanical interaction between an exoskeleton and its user. Here we showed that SLDS can generate the gait kinematics and the individual-specific responses to perturbations across all joints within a gait phase. Because the SLDS model represents gait dynamics as a linear systems, it may be useful for quickly forecasting future gait patterns, as is required for real-time control by rehabilitative robotics.

Our current and prior results show that SLDS can robustly identify gait phases in the presence of modeled and unmodeled gait perturbations. Identifying gait phases in the presence of disturbances is important for gait rehabilitation robotics, as robotic controllers are often designed for specific gait phases [2]. In our previous work, we demonstrated the relationship between SLDS discrete modes and gait phases for SLDS models without inputs [12]. Here we further showed that the inference of gait phases also holds when the perturbation is treated as an input to the model. The precision and recall values for gait phases we obtained in this work closely matched those of prior autonomous models.

Off-diagonal terms in each block of the SLDS dynamics matrices enabled long time horizon forecasting of gait kinematics. Here we showed that by explicitly including inter-joint coupling, SLDS models can forecast human gait using a small set of linear systems. Furthermore, the individual-specific joint coupling and responses to perturbation can be estimated and used to predict responses to perturbations affecting joint torques; in our case FES affected the joints, but our results could likely be generalized to the effects of applied torques from robotic exoskeletons. For longer time-horizons we showed the importance of including inter-joint coupling, which allowed joint kinematic trajectories to be forecasted over an entire gait cycle if gait event information is available. As such, the SLDS approach may be useful for controlling gait in real-time, allowing robot controllers to predict and adapt to interactions with the human.

SLDS provide a compact model of an individual's gait dynamics that can generate their response to perturbations. We showed that, within each gait phase, the SLDS can generate kinematic trajectories that match both an individual's unperturbed gait pattern and their unique response to a perturbation. While the perturbation was applied to directly affect right ankle flexion, its effects propagated multiple joints due to inter-joint coupling. Because SLDS models include joint coupling, they can capture and predict the inter-joint effects of single- or multi-joint perturbations. Purely

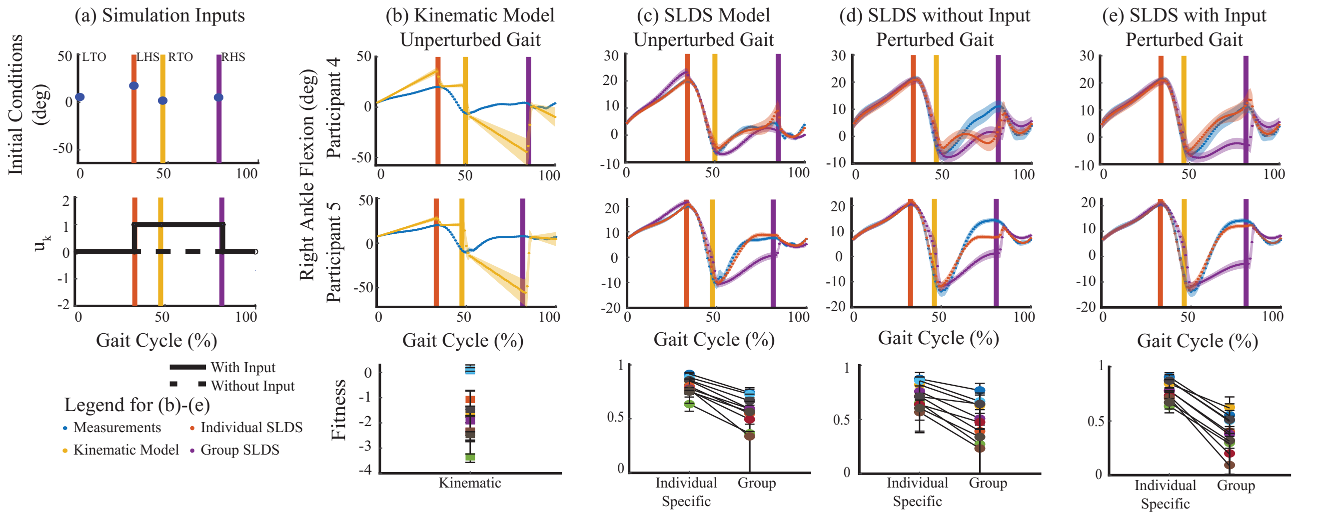

Fig. 2. SLDS predicts individual responses to FES perturbations to gait. Examples of time-normalized right ankle flexion from two of the five participants are given for comparison, and shaded regions indicate one standard deviation. Vertical bars indicate left heel-strike (red), right toe-off (yellow), and right heel-strike (purple) gait events. All traces start from left-toe off. (a) Inputs to the simulation include gait events, initial joint angles, and perturbation waveforms. (b) Gait trajectories generated by the kinematic model (yellow) compared to unperturbed gait measurements (blue). (c-d) Gait trajectories simulated by the SLDS model (red) without (c,d) and with input (e) compared to measured gait kinematics (blue) without (c) and with FES (d,e) perturbations, and to the group SLDS model (purple). Median fitness scores and the interquartile range for each condition are given for each joint angle.

statistical models of gait, which often do not include inputs [7], would be unable to generate such predictions.

Another advantage of our approach is that the SLDS models can be trained on a relatively small amount of gait data. We used approximately 1.5 minutes per individual, and while performance and generalizability may improve with more training data, the limited amount we used indicates that SLDS may be suitable for quickly modeling an individual's gait while using rehabilitative robotics. In practice, an SLDS model could be trained to represent the individual's gait dynamics and responses to robotic assistance from a short segment of data. The model could then be used to design individual-specific interactions while the device is in use.

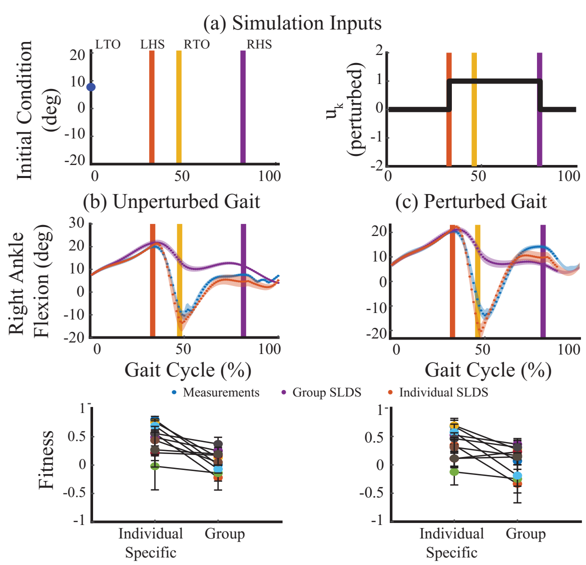

Fig. 3. Examples of individual-specific (red) and group (purple) SLDS simulations of a complete gait cycle compared to measured kinematics (blue) for one participant. (a) Generated trajectories start from left toe-off, and end at the left toe-off of the next gait cycle. Only initial conditions from left swing phase and the gait events were provided to the model. (b,c) Traces of time-normalized kinematics averaged over multiple gait cycles with standard deviations for both generating unperturbed (b) and perturbed (c) gait trajectories. Median fitness values with interquartile ranges for each joint angle across individuals are indicated for both models.

Modeling the dependence of gait phase on gait kinematics could improve the predictive performance of gait models based on SLDS by predicting the next ground contact event and smoothing out the gait kinematics near the transition point. When predicting across multiple gait phases, our SLDS model still requires the gait events to be specified beforehand; this is the case for other SLDS models of gait as well [9,10], because SLDS assumes the future gait phases will be independent of the future kinematics.

More work is required to generalize our results to account for different gait types, for the effects of different perturbations on gait, and for gait impairments. Our results were based on treadmill walking with electrical stimulation, and our models were trained on single speed walking in healthy young adults with only one type of perturbation. We also only modeled one amplitude of perturbation, which limited our ability to test the range of perturbations that could be modeled with SLDS. While these conditions could be used with treadmill-based rehabilitation robots [18,19], we do not yet know how the SLDS model would need to be modified to accommodate overground walking for robotic systems [20,21] where gait speed varies. Moreover, gait dynamics and individual responses to perturbations may become more complex with gait impairment. Currently, the ability of SLDS to model such gaits, and the range of the type and size of perturbations it can successfully predict, are unknown.

ACKNOWLEDGMENT

The authors thank Dr. Trisha Kesar of Emory University for her help in collecting the data used in this study.

REFERENCES

[1] Cao, J., et al. (2014). "Control strategies for effective robot assisted gait rehabilitation: the state of art and future prospects." Med Eng Phys 36(12): 1555-1566.

[2] Wang, L., et al. (2011). Model predictive control-based gait pattern generation for wearable exoskeletons. 2011 IEEE International Conference on Rehabilitation Robotics.

[3] Scholz, J. P. and G. Schner (1999). "The uncontrolled manifold concept: identifying control variables for a functional task." Experimental brain research 126(3): 289-306.

[4] Ting, L. H., et al. (2015). "Neuromechanical principles underlying movement modularity and their implications for rehabilitation." Neuron 86(1): 38-54.

[5] Ting, L. H. and H. J. Chiel (2017). "Muscle, Biomechanics, and Implications for Neural Control." Neurobiology of Motor Control: Fundamental Concepts and New Directions: 365-416.

[6] Clark, D. J., et al. (2009). "Merging of healthy motor modules predicts reduced locomotor performance and muscle coordination complexity post-stroke." Journal of Neurophysiology 103(2): 844-857.

[7] Aertbelien, E. and J. De Schutter (2014). Learning a Predictive Model of Human Gait for the Control of a Lower-limb Exoskeleton. Biomedical Robotics and Biomechatronics. Sao Paulo, Brazil, IEEE.

[8] Marchal-Crespo, L. and D. J. Reinkensmeyer (2009). "Review of control strategies for robotic movement training after neurologic injury." Journal of NeuroEngineering and Rehabilitation 6(1): 20.

[9] Babiarz, A., et al. (2015). "Mathematical Model of a Human Leg The Switched Linear System Approach." PECCS 2015 Proceedings of the 5th International Conference on Pervasive and Embedded Computing and Communication Systems: 90-97.

[10] Bissacco, A. and S. Soatto (2009). "Hybrid Dynamical Models of Human Motion for the Recognition of Human Gaits." International Journal of Computer Vision 85(1): 101-114. Proceedings. C. Schmid, S. Soatto and C. Tomasi. Los Alamitos, Ieee Computer Soc: 421-428.

[11] Pavlovic, V., et al. (2001). Learning switching linear models of human motion. Advances in Neural Information Processing Systems 13. T. K. Leen, T. G. Dietterich and V. Tresp. Cambridge, M I T Press. 13: 981-987.

[12] Baptista, R. D., et al. (2017). "Automatic Human Movement Assessment With Switching Linear Dynamic System: Motion Segmentation and Motor Performance." Ieee Transactions on Neural Systems and Rehabilitation Engineering 25(6): 628-640.

[13] Drnach, L., Essa, I., and Ting, L.H. (2018). "Identifying Gait Phases from Joint Kinematics during Walking with Switched Linear Dynamical Systems." Biomedical Robotics and Biomechatronics. Enschede, The Netherlands, IEEE.

[14] Bissacco, A. (2005). Modeling and learning contact dynamics in human motion. 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Vol 1, Proceedings. C. Schmid, S. Soatto and C. Tomasi. Los Alamitos, Ieee Computer Soc: 421-428.

[15] Reisman D, Kesar T, Perumal R, Roos M, Rudolph K, Higginson J, Helm E, Binder-Macleod S. Time course of functional and biomechanical improvements during a gait training intervention in persons with chronic stroke. J Neurol Phys Ther (2013) 37:159165.

[16] Chiang, J., et al. (2008). "A Hidden Markov, Multivariate Autoregressive (HMM-mAR) Network Framework for Analysis of Surface EMG (sEMG) Data." IEEE Transactions on Signal Processing 56(8): 4069-4081.

[17] Rabiner, L. R. (1989). "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition." Proceedings of the IEEE 77(2): 257-286.

[18] Banala, S. K., et al. (2009). "Robot assisted gait training with active leg exoskeleton (ALEX)." Ieee Transactions on Neural Systems and Rehabilitation Engineering 17(1): 2-8.

[19] Veneman, J. F., et al. (2007). "Design and evaluation of the LOPES exoskeleton robot for interactive gait rehabilitation." Ieee Transactions on Neural Systems and Rehabilitation Engineering 15(3): 379-386.

[20] Banala, S. K., et al. (2009). "Robot assisted gait training with active leg exoskeleton (ALEX)." Ieee Transactions on Neural Systems and Rehabilitation Engineering 17(1): 2-8.

[21] Kazerooni, H., et al. (2005). On the Control of the Berkeley Lower Extremity Exoskeleton (BLEEX). Proceedings of the 2005 IEEE International Conference on Robotics and Automation.