Do Switched Linear Dynamical Systems Provide Robust Kinematic Predictions of Healthy Treadmill Gait at Different Speeds?

I. INTRODUCTION

Machine learning methods can classify different gait patterns, demonstrating that they encode different dynamics. Recently, data-driven SLDS models have been used to predict the transitions between single and double support gait phases. SLDS models can also predict joint kinematics over relatively long time horizons. However, we do not know whether these models generalize across walking speeds. Here we tested the ability of SLDS models trained on an individual’s kinematic data at a single speed to effectively reconstruct kinematic data of different gait speeds.

II. METHODS

Two healthy individuals (1 males/1 female, 28±1 year) were enrolled in this pilot study. Participants walked on a treadmill at a comfortable self-selected speed, and at a fast speed. Kinematic data was collected at 100 Hz using a 7-camera Vicon system and forces collected at 2000 Hz using an instrumented dual-belt treadmill. We used SLDS to model the bilateral lower limb joint angle trajectories during gait. An SLDS is a set of linear dynamical systems with discrete modes that govern when to switch between the individual linear models using Hidden Markovian model approach. Specifically, we used an autoregressive SLDS, which can be written as in (1).

\[ x_{k+1} = A_{z_k} x_k + w_k(z_k) \]

Where \( z_k \in \{1, ..., N\} \) is the discrete mode, \( x_k \) is the state vector at time step \( k \), \( A_{z_k} \) is the linear system parameters and \( w_k(z_k) \) is a zero-mean, Gaussian noise term [2]. We trained an SLDS with four discrete modes on 9 trials of each participant’s gait data at one speed and tested the model’s ability to predict gait phases and kinematics at different speeds.

III. RESULTS AND DISCUSSION

Training and testing SLDS models (n=6) on datasets of the same gait speed of 0.9 mps resulted in an average phase prediction (aPPA) of 92.76% ± 0.70 % and average root mean square error (aRMSE) over all joint angle reconstructions of 3.26 ± 0.57˚ (range: 1.22˚ -7.96˚). When testing these models on 1.3 mps speed data (n = 9), the aPPA decreased by 0.17% and aRMSE increased by 166.87% (range: 4.36˚ – 17.79˚). Training and testing SLDS models (n=6) on the same gait speed of 1.3 mps resulted in aPPA of 96.85% ± 0.80% and aRMSE 2.90˚ ± 0.40˚ (range: 1.24˚ -6.55˚). When testing these models on 0.9 mps speed data (n = 9) the aPPA decreased by 4.7% and the aRMSE increased by 161% (range: 3.80˚-16.49˚). Although SLDS results in high phase segmentation accuracy, Fig. 1 shows that it does not have great kinematic prediction a gait speed different gait than the one it was trained on.

IV. CONCLUSION

Despite the ability of SLDS to model with high gait phase prediction accuracy (>92%) across different speeds, kinematic predictions do not appear to be generalizable across different speeds for the same individual. Future studies will evaluate methods to improve generalization of these models across speeds and walking conditions.

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REFERENCES
