Discrepancy Modeling for Human Locomotion

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Introduction

Despite our ability to model the human system, accurately predicting locomotion when idealized musculoskeletal model dynamics differ from reality remains challenging. While first-order, physics-based models describing human motion generally capture salient characteristics of locomotion, physical systems are not ideal. Thus, models are unable to capture the complete dynamics observed in experiment, i.e. simulation does not match experiment [1, 2]. The inability to represent such discrepancies can have significant impact on model predictions.

Discrepancies can arise from a variety of factors often ignored in idealized models, such as with parameter mismatch (subject-specific musculotendon properties, segment mass estimation error) or missing physics (unmodeled body segments, motion artifacts, soft tissue mechanics). These discrepancies are typically unique to an individual and must be learned and quantified as such. Taking inspiration from perturbation theory [3], we develop a mathematical architecture based upon sparse regression that discovers interpretable, data-driven discrepancy models to augment first principles dynamics that may help predictions and guide future experimental studies. To evaluate the feasibility of discrepancy models in human locomotion, we used a simple dynamic walking model in an ideal simuation environment and hypothesized our simulation framework would recover small nonlinear discrepancies from the model's locomotion dynamics.

Methods

The sparse identification of nonlinear dynamics (SINDy) algorithm [1] uses sparse regression to discover a parsimonious representation of nonlinear system dynamics from measurement data. An important assumption about the model structure is that there are only a few salient terms governing the dynamics; this ensures system interpretability and avoids overfitting. Recently, this framework has been used to identify discrepancy models between empirical data and model outputs of a system [2]. Discrepancy models can analogously be thought of as a first-order perturbation model. Our solvable problem (A_0) is an oscillatory 2-link pendulum [4] with collision constraints, and the first-order perturbation solution ($\tilde{A}$) includes small nonlinear contributions to equations of motion $A \approx A_0 + \tilde{A}$ where $\tilde{A} \ll 1$.

We used a simple passive dynamic walking model described by two states: θ *(angle of stance leg w.r.t. vertical)* and φ *(relative angle between legs)* (Fig. 1). N = 1000 trials were performed. Each trial generated a random polynomial discrepancy (max. order 5) and randomly added the discrepancy to a system state. Kinematics were evaluated for stability (10+ steps) before using SINDy to recover the discrepancy model.

Results and Discussion

SINDy recovered first-order physics with high fidelity, correctly identifying 88.6% of the discrepancies. No discrepancy model was identified for the remaining 11.4% due to an inappropreiatly high sparcity regularization parameter. This could be rectified in future analyses via hyperparameter tuning.

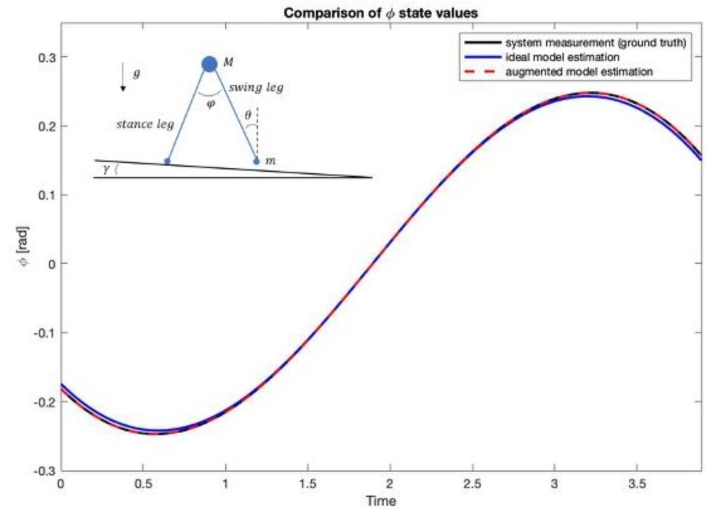

Figure 1: Model parameter φ for one step. Ideal model estimation (blue) fails to fully capture measured system dynamics (black). Discrepancy model augments the ideal model (dashed red) to recover system physics.

While this initial investigation used a simple toy model to investigate the use and accuracy of discrepancy modeling for recovering locomotion dynamics, including system-specific corrections to an idealized model can help close the gap between experiment and simulation.

Significance

This work is a critical first step in improving the integration of heterogeneity into musculoskeletal models to improve prediction accuracy. Developing subject-specific models will be crucial for predicting effects of treatments or interventions computationally. This is especially true when an individual has a motor impairment and does not subscribe to the same assumptions about musculoskeletal properties as unimpaired individuals.

Acknowledgments

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