Biomechanically-Constrained Machine Learning for the Identification of Discrepancy Models

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What is Discrepancy Modeling?

A **discrepancy** is an error between an estimated and true state value.

Discrepancies occur when there are missing physics or parameter mismatch(es) in first-principle modeling of physical systems.

Discrepancy modeling assumes an underlying mechanistic structure to inform the learning of model identification. First-order physics-based models generally capture salient characteristics, and while such models are ideal representation of a non-ideal system, they provide a meaningful foundation to start building a model to capture true, not just estimated, dynamics. The inability to represent discrepancies in simulations can have significant impact on model prediction and performance [1, 2].

It suggests a narrative other than black-box modeling of experimental data for predicting dynamics when prior knowledge of a system is present. While we don't often know everything about a complex system, we usually don't know nothing.

Broad goal: test an arsenal of algorithms to learn discrepancy models that describe the error between estimated/ideal dynamics and measured system states. find advantages & limitations of each

Discrepancy Modeling for Bipedal Locomotion

Discrepancy modeling for humans is challenging, as heterogeneity suggests discrepancy models are unique, and thus must be learned and quantified as such.

Our overarching goal is to adapt previously developed data-driven modeling architectures to identify discrepancy models to provide system-specific corrections to more accurately capture system behavior.

Further, we intend to provide guidance as to which algorithm may work best depending on factors including stochastic noise levels, data availability, forecasting window, feedback control, and interpretability/generalizability.

The first algorithm we test is a mathematical architecture based upon sparse regression[1,3] that discovers interpretable, data-driven discrepancy models to augment first-principle dynamics. This may aid in more accurate locomotion predictions and improve robust control and stability performance.

Feasibility of Sparse Regression for Bipedal Dynamics

We used a simple dynamic walking model in an ideal simulation environment and hypothesized our simulation framework would recover small nonlinear discrepancies from the model's locomotion dynamics.

Goal: apply a known discrepancy to an ideal system and use SINDy to recover the discrepancy dynamics

No discrepancy
No noise
Noise

*** use stance phase dynamics

basically use my presentation from last week to build the methods & results

Discussion

This work is a critical step in integrating heterogeneity into musculoskeletal and robotic models to improve prediction accuracy and ensure robust performance.

- Hyperparameter tuning could improve discrepancy model identification capabilities
- Choosing potential library terms requires some level of system knowledge
- SINDy identifies discrepancies quite well in an ideal environment; noise may complicate model recovery due to noise amplification in numerical differentiation

Next Steps

- Gaussian Process Regression
- Dynamic Mode Decomposition

References

1. Brunton, S et al., *PNAS*, 113(13): 3932-3937, 2016.
2. Kaheman, K et al., *arXiv:1909.08574*, 2019.
3. Bender & Orzag, *Adv. Math. Methods Sci.,Eng.*, Springer: 1999, 61-145.
4. McGeer, T, *Int. J. Robot*. Res, 9(2): 62-82, 1990.

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