DISCREPANCY MODELING IN BIPEDAL DYNAMICS

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The Challenge

Accurately predicting locomotion using idealized model dynamics remains challenging. While first-order, physics-based models describing human or robotic systems generally capture salient characteristics of locomotion, **physical systems are not ideal.**

Discrepancies can arise due to:
- missing physics
- parameter mismatch

Discrepancies are typically unique to an individual or robotic system and must be learned and quantified as such. Further, the inability to represent the discrepancy between simulation and observation can have significant impact on model prediction and performance [1, 2].

We develop 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.

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.

Methods

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

Sparse Identification of Nonlinear Dynamics (SINDy) [1]

$$\mathbf{X} = \left[\mathbf{x}(t_1)\ \mathbf{x}(t_2)\ \dots\ \mathbf{x}(t_m)\right]^T\ \mathbb{R}^{m\times n}$$ measurements

$$\dot{\mathbf{X}} = \left[\dot{\mathbf{x}}(t_1)\ \dot{\mathbf{x}}(t_2)\ \dots\ \dot{\mathbf{x}}(t_m)\right]^T\ \mathbb{R}^{m\times n}$$

$$\mathbf{\Theta}(\mathbf{X}) = \left[\theta_1(\mathbf{X})\ \theta_2(\mathbf{X})\ \dots\ \theta_v(\mathbf{X})\right]^T \in \mathbb{R}^{m\times v}$$ library of potential terms (e.g. polynomial or trigonometric)

$$\dot{\mathbf{X}} = \mathbf{\Theta}(\mathbf{X})\mathbf{\Xi}$$

$$\mathbf{\Xi} = \left[\xi_1\ \xi_2\ \dots\ \xi_v\right] \in \mathbb{R}^{v\times n}$$ sparse coefficients of library terms

SINDy for Discrepancy Modeling

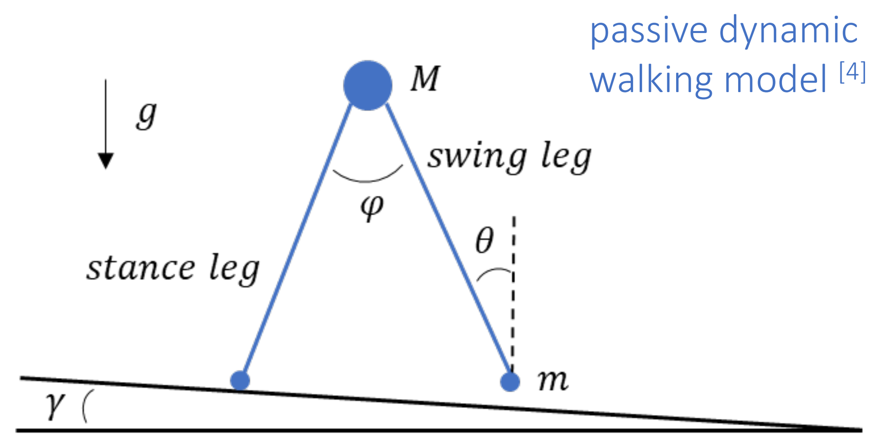
$$\dot{\mathbf{X}}_0 = f(\mathbf{x})$$ ideal system dynamics

$$\dot{\mathbf{X}}_m = f_m(\mathbf{x})$$ passive dynamic walker [4]

$$f(\mathbf{x}) \neq f_m(\mathbf{x})$$

$$\delta\dot{\mathbf{X}} = \dot{\mathbf{X}}_0 - \dot{\mathbf{X}}_m = \mathbf{f}(\mathbf{x}) - \mathbf{f}_m(\mathbf{x}) = \mathbf{g}(\mathbf{x})$$ discrepancy model

$$\delta\dot{\mathbf{X}} = \mathbf{\Theta}(\mathbf{X})\mathbf{\Xi}$$ SINDy algorithm [1]



States
θ = angle of stance leg w.r.t. vertical
ϕ = relative angle between legs

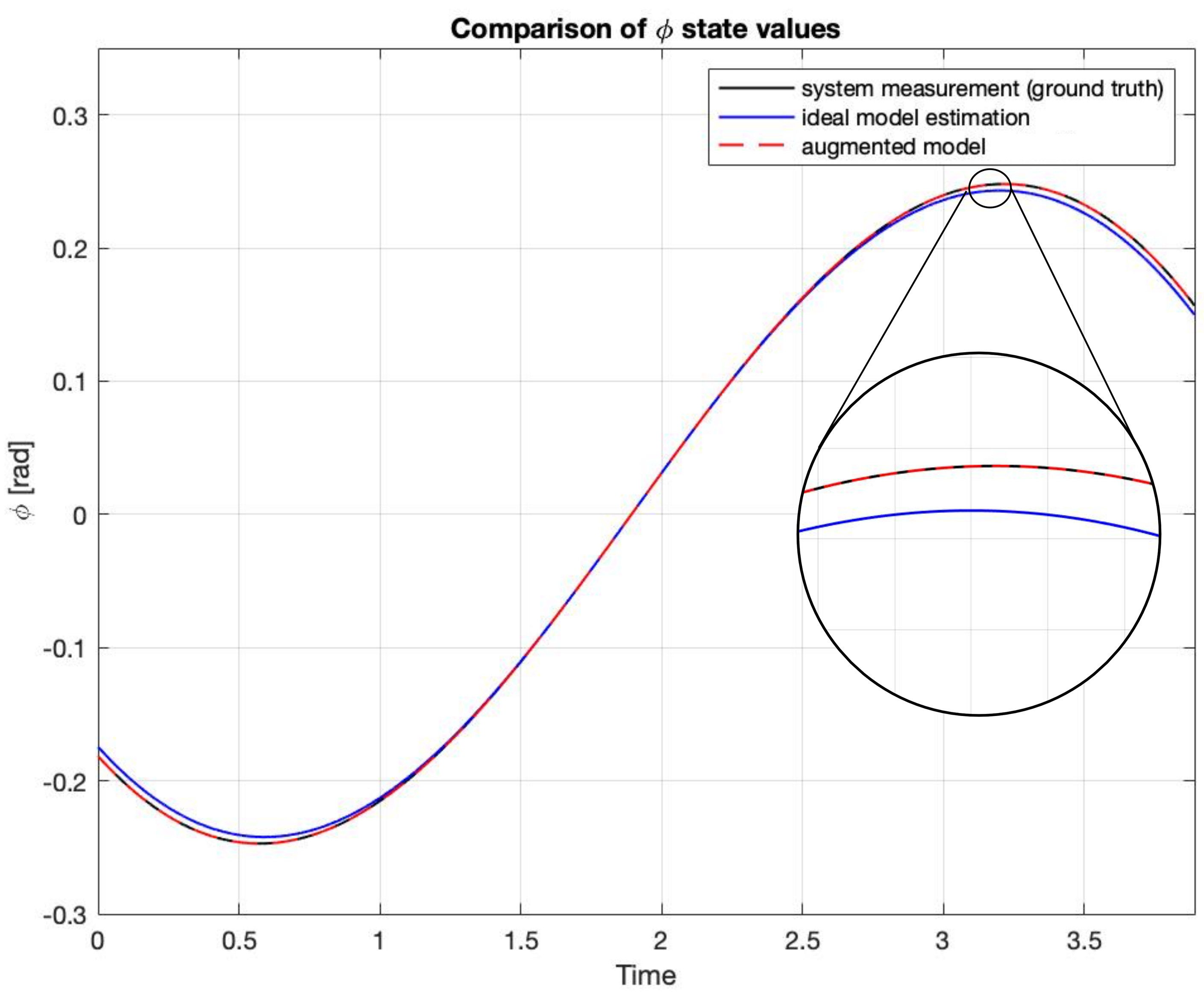
Trials
N = 1000

Algorithm
1. Generate a random polynomial discrepancy (max. order 5)
2. Randomly add the discrepancy to one of the model's system states
3. Evaluate kinematics for stability (10+ steps)
4. Use SINDy to recover the discrepancy dynamics
5. Augment the ideal model with the discrepancy model

Results

SINDy recovered discrepancy dynamics with high fidelity

- 88.6% of the discrepancies were correctly identified
- No discrepancy model was identified for the remaining 11.4% due to an inappropriately high sparsity regularization parameter



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

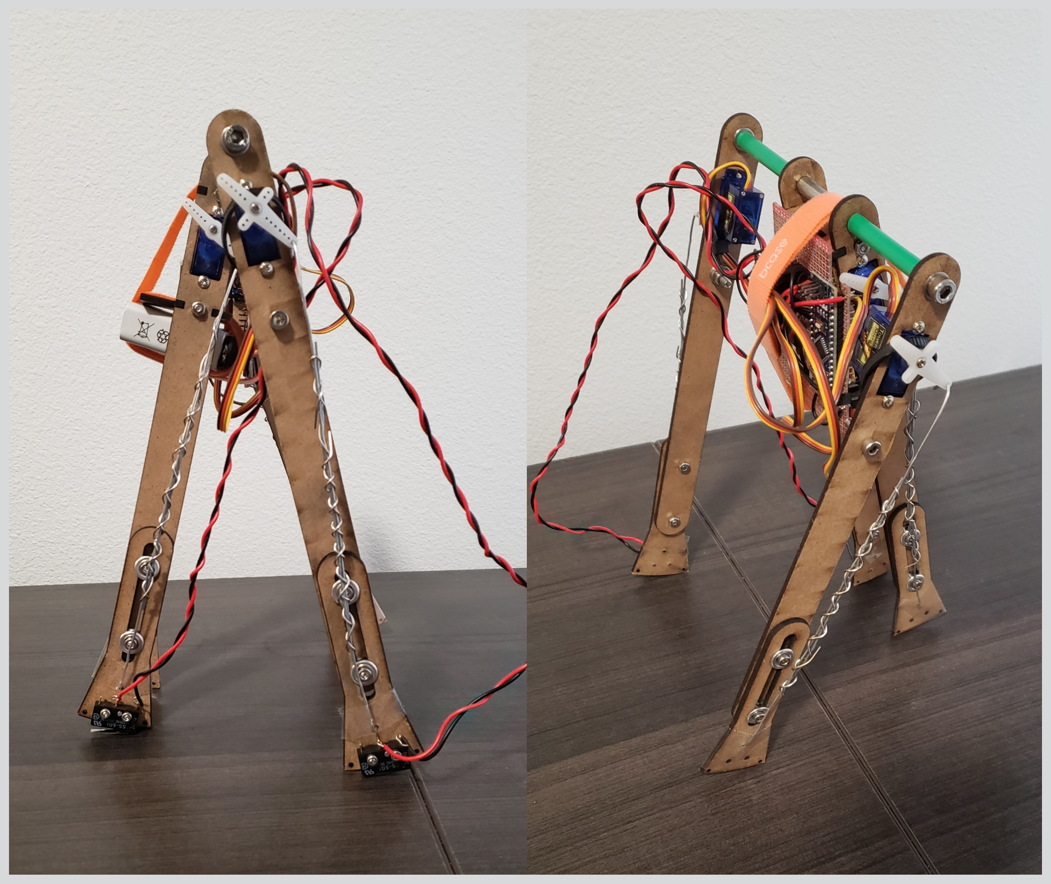
Next Steps

Theoretical

- increase model complexity (actuation, knees)
- add contact modeling
- add noise filtering/identification

Experimental

- collect experimental data from a bipedal robot to validate the simulation framework



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Acknowledgments

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