FY25 Strategic University Research Partnership (SURP)

Physics-Guided Deep Learning for Interpretable Parachute System Dynamics

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Objectives. The goal of this project is to use physics-guided deep learning methods for data-driven discovery of parachute dynamics. Our approach is to use a grey-box neural network (NN)-based model which incorporates knowledge of the system dynamics and amends it with a NN to capture residual dynamics in a structured way.

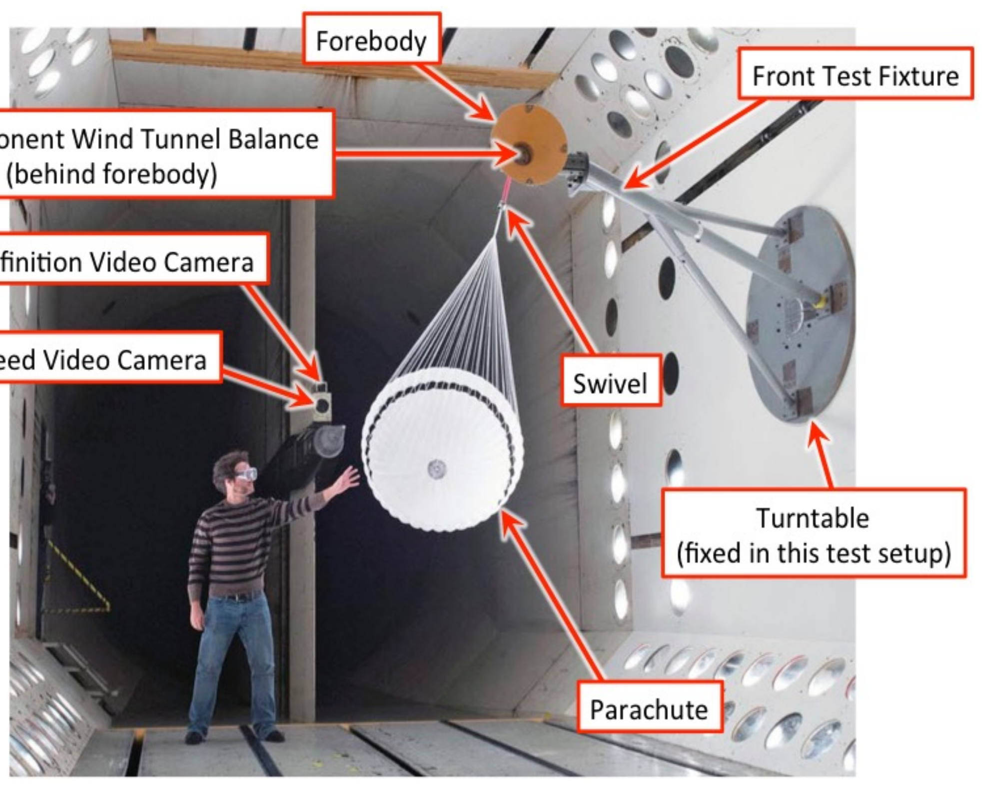

Figure 1. Experimental setup from 2014 wind tunnel test.

Background. Almost every Planetary Entry, Descent, and Landing (EDL) sequence to date has included one or more parachute descent phases, where events critical to the safety of the mission took place. Understanding the dynamics of the parachute/capsule system is critical to the successful design and execution of the EDL sequence. However, existing models for parachute system dynamics are known to be incomplete, and do not accurately predict the evolution of the parachute for extended time horizons. While Deep Neural Network (DNN) models can capture complex dynamics, their solutions preclude any meaningful interpretation. At the intersection of dynamics and DNN researchers have developed models using physical constraints [1] to yield better generalization and interpretability.

Approach and Results. Models are evaluated using a dataset of subscale parachute models captured at the Transonic Dynamics Tunnel [2]. Forces were captured at 600Hz and video at 120Hz. The experimental data presents challenges typical of real-world data: obstructed views, noisy measurements, low frame rates, and incomplete state information. To circumvent these challenges in model evaluation, we develop a simulator to generate trajectories from experimental force measurements (see Figure 2).

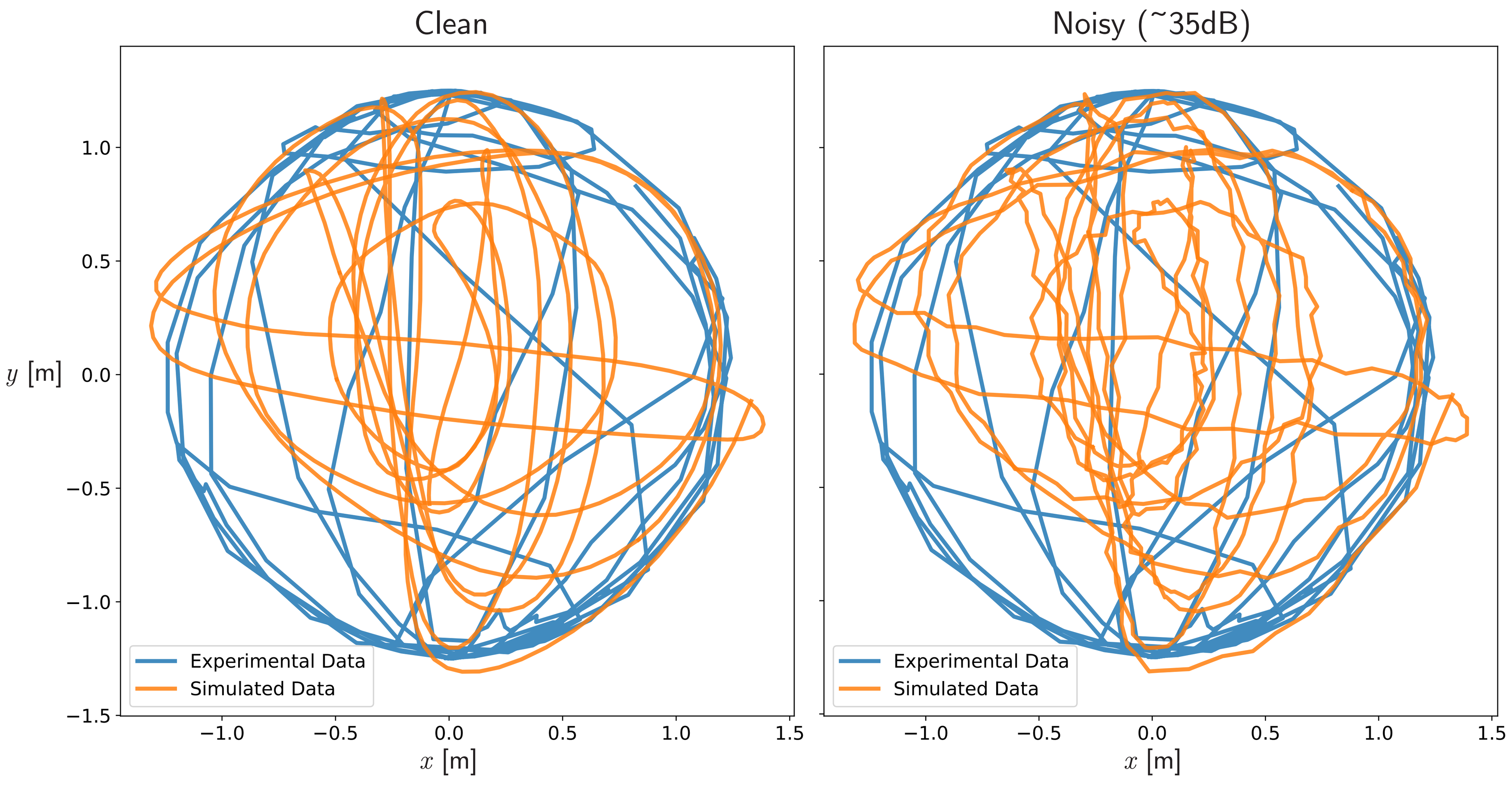

Figure 2. Comparison of simulated (orange) and real (blue) trajectories. The empirical KL-divergence between the two trajectory is 18.49, indicating good consistency of the synthetic data.

We focus on the 4 methods illustrated in Figure 3 to understand existing methods' ability to model parachute dynamics:

- MultiLayer Perceptron (MLP) maps input directly to output;
- Neural Ordinary Differential Equations (NeuralODE) [3] uses a NN to model the right-hand side of an ODE;
- Lagrangian Neural Network (LNN) [4] uses a NN to parameterize a system Lagrangian and updates system states using the Euler-Lagrange equation;
- LNN + Residual uses NeuralODE to capture residual dynamics resulting from con-conservative forces.

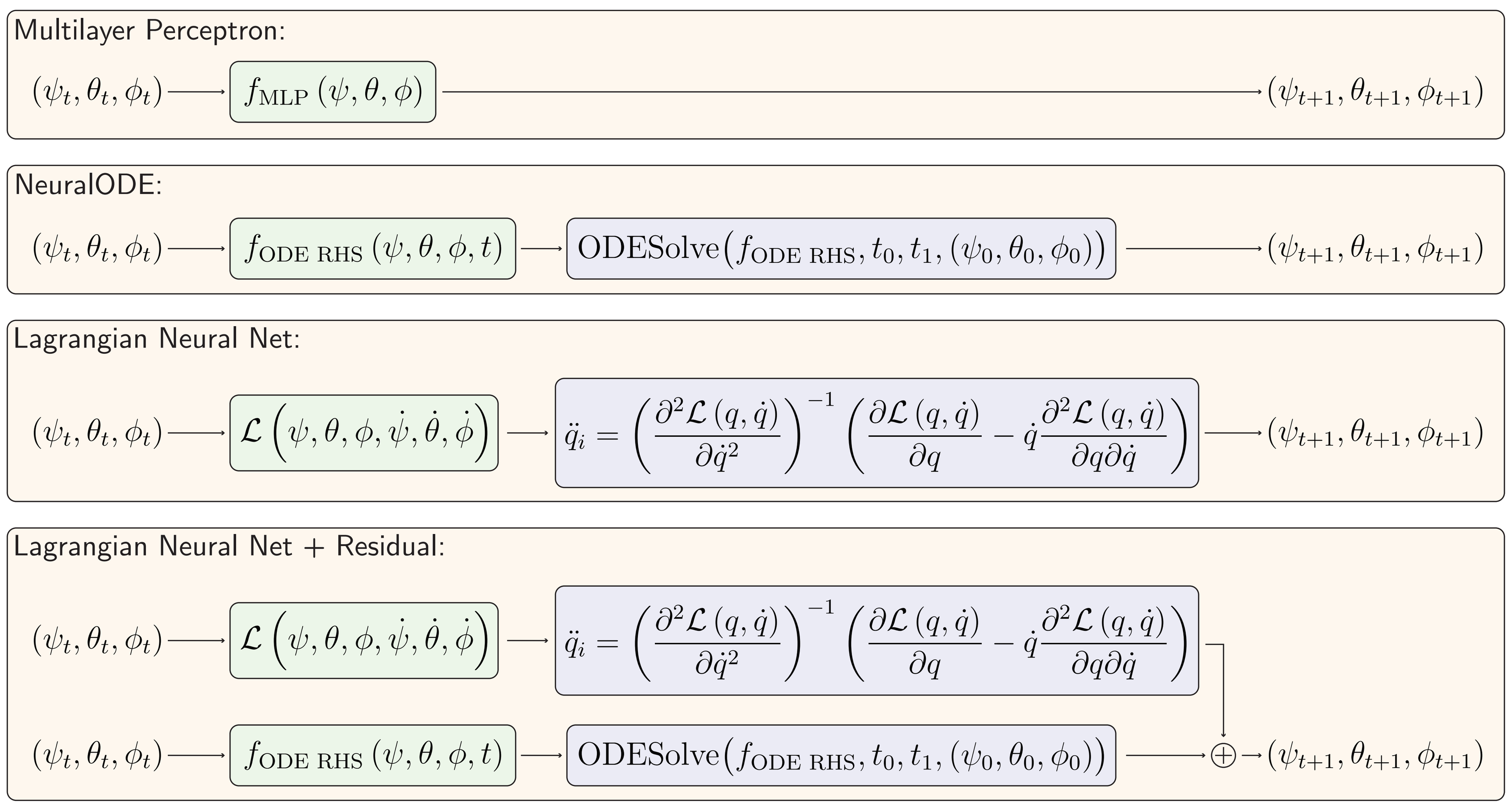

Figure 3. Comparison of baseline models.

In Figure 4 and Table 1 the models are assessed in terms of accuracy (Mean Square Error) and distribution similarity (KL-divergence). MLP's performance deteriorates on low framerates due to spectral bias favoring low-frequency solutions. NeuralODE performs well on both framerate as it derives its dynamics from ODEs but offers little interpretability. LNN fails since the simulated parachute is not a conservative system due to external forcing.

Our LNN+Residual model consists of an LNN to capture dynamics of the parachute and a NeuralODE to model external forcing. It predicts the most accurate and consistent low framerate trajectories while performing on par with black-box models on high framerate trajectories.

Table 1. Quantitative comparison of predicted trajectory at high and low framerate.

	High Framerate (600Hz)			
	MLP	**NeuralODE**	**LNN**	**LNN + Residual**
MSE	2.73×10^{-5}	3.94×10^{-5}	2.79×10^{-2}	3.36×10^{-5}
KL	0.006	0.022	34.22	0.015
	Low Framerate (120Hz)			
	MLP	**NeuralODE**	**LNN**	**LNN + Residual**
MSE	2.69×10^{-2}	6.01×10^{-4}	1.31×10^{-1}	9.10×10^{-5}
KL	55.74	27.61	54.23	12.54

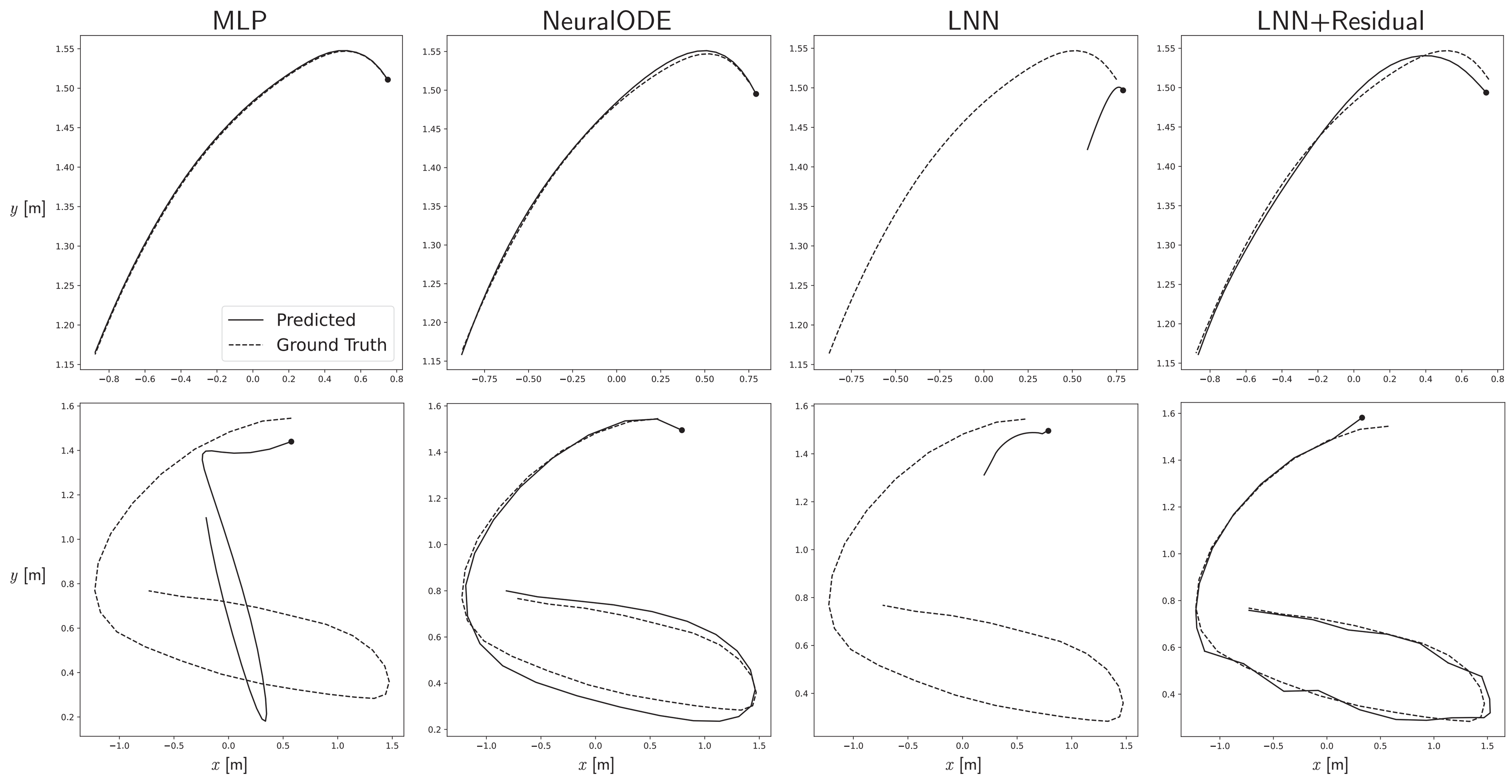

Figure 4. Qualitative comparison of predicted trajectory at high (top row) and low (bottom row) framerate.

Benefit to JPL. To date, missions have dealt with the uncertainties in on-chute dynamics by conservatively designing hardware, at the cost of large mass and timeline margins. Developing improved models for parachute/capsule dynamics will allow NASA/JPL to reduce conservatism and address design challenges directly. For example: enabling higher landed mass Mars missions (MSR, human precursor); implementing novel EDL architectures such Mid-Air Helicopter Deployment, modeling separation conditions for low-cost hard landers. Furthermore, this collaboration will strengthen JPL's capabilities in the of data-driven modeling and machine learning.

References:

[1] Frank M White and Dean F Wolf. A theory of three-dimensional parachute dynamic stability. Journal of Aircraft, 5(1):86–92, 1968. [2] C. H. Zumwalt, J. R. Cruz, D. F. Keller, and C O'Farrell. Wind Tunnel Test of Subscale Ringsail and Disk-Gap-Band Parachutes. AIAA Paper, (2016-3426), 2016. [3] Ricky TQ Chen, et al. Neural Ordinary Differential Equations. Advances in Neural Information Processing Systems, 2018. [4] Miles Cranmer, et al. Lagrangian Neural Networks. arXiv, 2020.

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