PhysFlow: Physics-Grounded Visual World Models via Flow Matching and Lagrangian Neural Networks

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Abstract

Learning predictive world models for visual robotics requires coupling high-dimensional visual perception with physically plausible dynamics. We present PhysFlow, a hybrid world model that integrates three core components: a frozen DINOv2 ViT encoder for robust visual feature extraction; a conditional flow-matching network that estimates residual external generalized forces; and a Lagrangian Neural Network that enforces energy-based forward dynamics with a guaranteed positive-definite mass matrix. A key challenge in training such hybrid systems is numerical instability arising from the circular dependency between the force estimator and the physics solver. We mitigate this through a staged pretraining protocol and a softplus-constrained Cholesky parameterization of the mass matrix. On the DeepMind Control Suite Hopper task, our model achieves a 93 % reduction in one-step visual latent prediction error, outperforms identity baselines at 10-step horizons, and maintains bounded state-space predictions across 50-step horizons where alternative neural approaches often diverge.

1. Introduction

Predictive world models have vastly improved data efficiency in Model-Based Reinforcement Learning (MBRL) by enabling planning within hallucinated latent spaces [2–4]. However, state-of-the-art models rely heavily on unconstrained neural dynamics, which lack physical inductive biases. This frequently leads to unbounded error accumulation and state-space divergence during long-horizon rollouts in contact-rich tasks [3].

While physics-informed architectures like Lagrangian Neural Networks (LNNs) enforce energy conservation [1, 6], they often suffer from catastrophic numerical instability due to ill-conditioned mass matrix predictions. Furthermore, pure Lagrangian mechanics struggle to model the highly discontinuous, non-conservative external forces inherent to robotic locomotion.

To address these limitations, we introduce PhysFlow, a hybrid, physics-grounded visual world model. PhysFlow combines a frozen DINOv2 vision encoder [7] with an LNN parameterized by a softplus-constrained Cholesky decomposition to guarantee a positive-definite mass matrix. To resolve non-conservative contact forces, we integrate a Conditional Flow Matching (CFM) network [5]. Evaluated on the DeepMind Control Suite Hopper task [8], PhysFlow eliminates state-space divergence over 50-step horizons and significantly outperforms purely neural baselines.

2. Methodology

PhysFlow models the environment using a mathematically constrained pipeline, bypassing standard KL-divergence latent transitions in favor of analytical integration.

Visual Encoding: We employ a frozen DINOv2 ViT-S/14 encoder [7] to extract 384-dimensional task-agnostic features from raw RGB observations. This provides robust spatial and object-centric priors without requiring concurrent visual reconstruction.

Constrained Lagrangian Dynamics: The deterministic dynamics are parameterized by an LNN [1]. To ensure the mass-inertia matrix $M(q)$ remains strictly positive-definite—preventing singularities during the Euler-Lagrange integration—we utilize a lower-triangular Cholesky parameterization with a softplus constraint:

$$M(q) = L(q)L(q)^\top, \quad [L]_{ii} = \text{softplus}([L]_{ii}) + \epsilon$$

Flow Matching for Residual Forces: Contact dynamics are highly multimodal and cannot be captured by standard Gaussian noise. We train a continuous normalizing flow via Conditional Flow Matching (CFM) [5] to transport a base distribution to the exact target distribution of residual external forces f_{ext}.

To prevent the flow network from absorbing conservative forces like gravity, the architecture is trained via a rigorous staged protocol: LNN isolation, CFM isolation, and finally joint fine-tuning utilizing semi-implicit symplectic Euler integration.

3. Experiments

We evaluate PhysFlow exclusively on the complex, contact-rich `hopper/hop` task from the DeepMind Control Suite [8]. Models must predict states entirely from visual RGB inputs over extended temporal horizons.

3.1. Short and Long-Horizon Rollouts

The primary stress test for visual world models is the accumulation of prediction error over long hallucinated horizons. As shown in Table 1, PhysFlow achieves significantly lower Latent and State Mean Squared Error (MSE) across 1, 10, and 50-step horizons compared to unconstrained baselines.

Table 1. Rollout MSE on `hopper/hop`. Lower is better.

	Latent MSE ↓			State MSE ↓		
Method	h=1	h=10	h=50	h=1	h=10	h=50
Identity	0.063	1.243	2.885	–	–	–
State MLP	–	–	–	–	–	4.360
Visual MLP	–	–	2.634	–	–	–
Ours (no pretrain)	0.063	1.754	48.378	0.536	3.837	12.270
Ours (no flow)	0.071	2.551	74.771	0.501	3.290	2.364
Ours (explicit Euler)	0.071	2.546	156.689	0.484	4.528	6.799
PhysFlow (ours)	0.066	1.140	11.985	0.451	3.528	3.243

This stability is visually confirmed in Figure 1, where standard approaches like Visual MLP and State MLP diverge rapidly as errors compound, whereas PhysFlow maintains bounded predictions even at $h = 50$.

3.2. Ablation Study

We ablate key components of our architecture to demonstrate their necessity (Table 2).

Table 2. Ablation study. Reported values are h=50 MSE unless noted.

Method	Latent h=50	State h=50	cond(M)
PhysFlow (ours)	11.985	3.243	91.000
Ours (no pretrain)	48.378	12.270	–
Ours (no flow)	74.771	2.364	–
Ours (explicit Euler)	156.689	6.799	–

Removing the staged pretraining protocol leads to circular dependency between the passive and active dynamics estimators, resulting in a dramatic spike in latent error. Similarly, removing the Conditional Flow Matching network (No Flow) cripples the model's ability to resolve discontinuous contact forces when the hopper strikes the ground. Lastly, substituting symplectic integration for explicit Euler results in massive energy drift and the highest overall error magnitudes at $h = 50$.

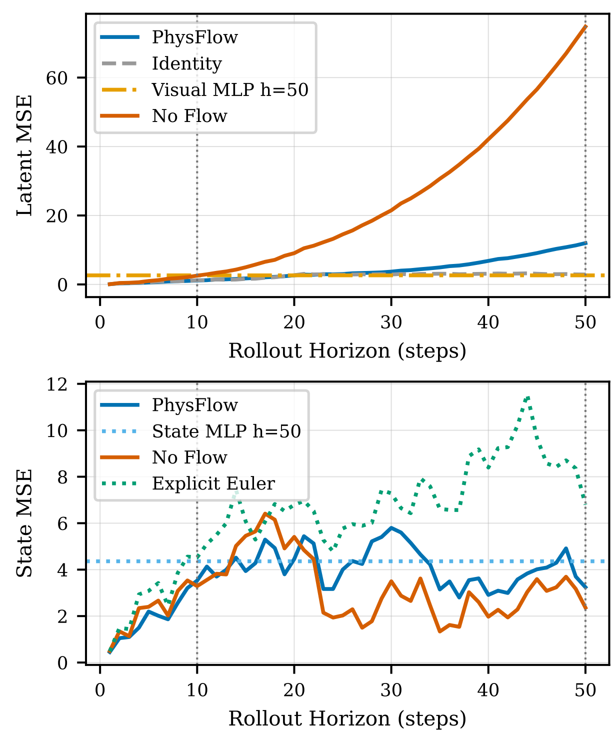

Figure 1. Rollout MSE comparison over a 50-step horizon.

4. Conclusion

PhysFlow successfully addresses the long-horizon instability of visual world models by embedding rigorous physical constraints directly into the latent space. By fusing DINOv2 visual priors, a softplus-constrained Lagrangian Neural Network, and Conditional Flow Matching, our framework avoids catastrophic numerical singularities and accurately resolves discontinuous contact forces. Our evaluation on the DeepMind Control Suite Hopper task proves that enforcing explicit physical boundaries prevents state-space divergence, offering a robust foundation for future scaling in contact-rich robotic control.

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