
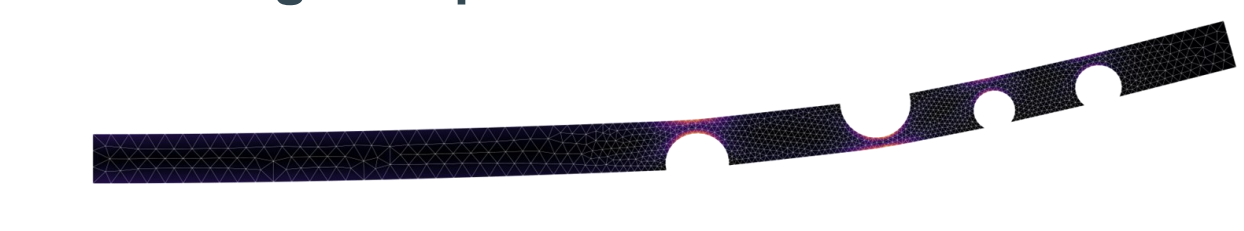






Diffusion-Based Hierarchical Graph Neural Networks for Simulating Nonlinear Solid Mechanics

Challenges

Message Passing Bottleneck

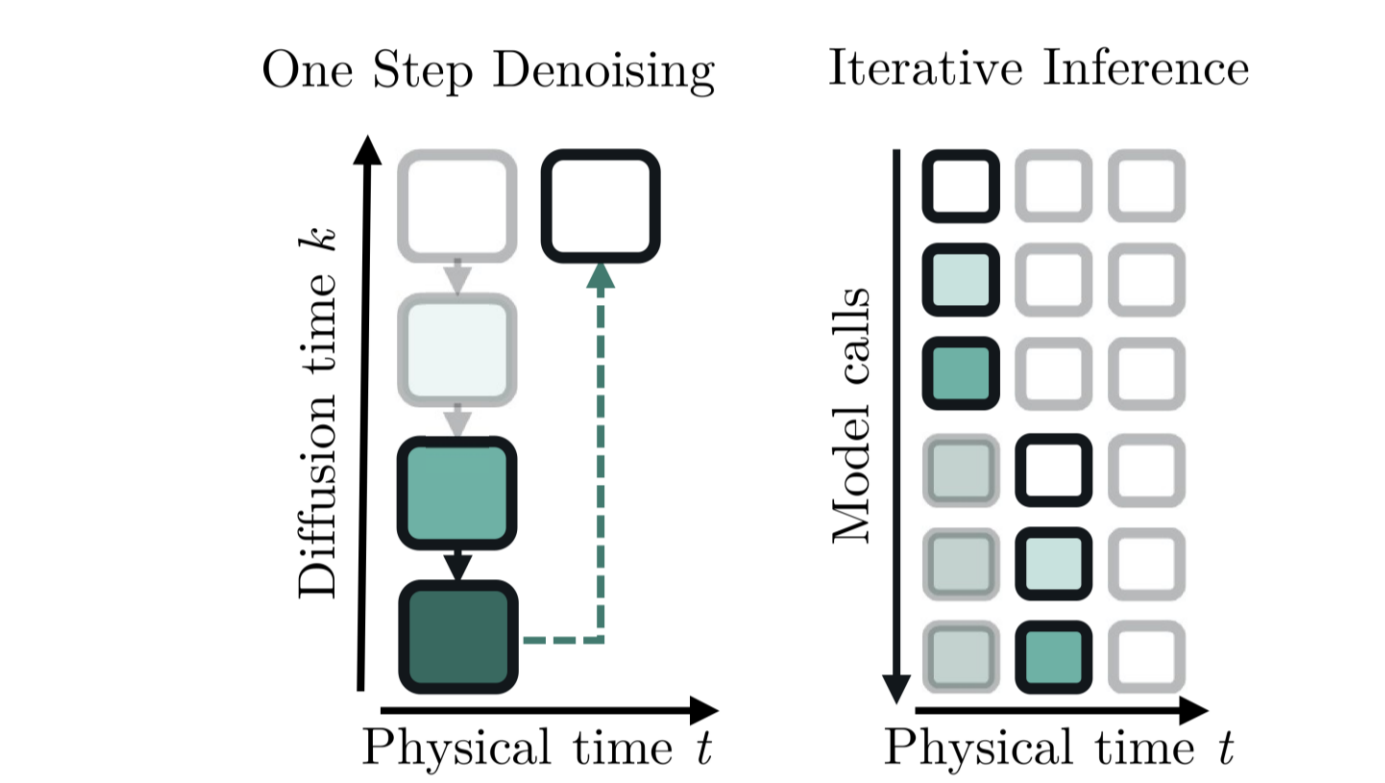
- Local boundary conditions...

- ... cause global part deformations

- Local Information has to be propagated globally
- However, Message Passing Layer act locally
- Infeasible for large (mesh-) graphs / graph diameters


Spectral bias of MSE-trained Model

- Ground truth

- Prediction with low frequency bias

- Prediction with high frequency bias

- Conventional MSE-based training is more sensitive to global deformation deviations than to local mesh distortions (spectral bias)

Conventional Denoising

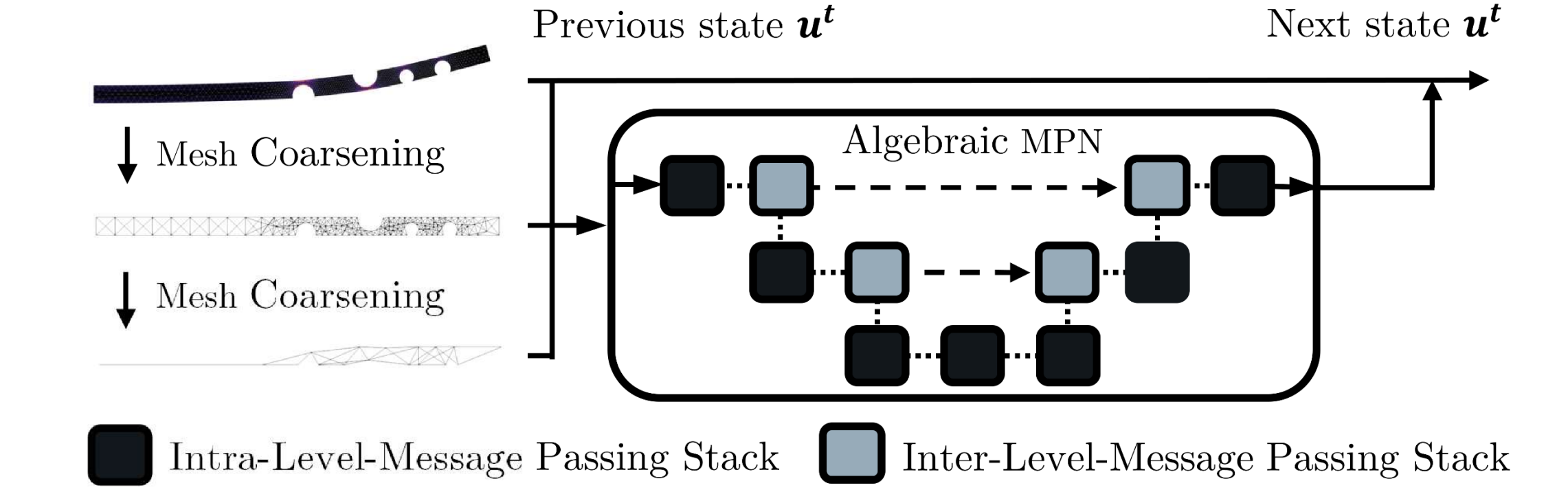
- Conventional diffusion-based simulators denoise step-wise
→ $\sigma(KT)$ for K diffusion and T physical steps



ROBIN: Rolling diffusion-Batched Inference Network

Algebraic hierarchical Message Passing Networks

- Maximized receptive field – One cycle propagates information across the entire mesh
- Increase prediction fidelity by multiscale message passing
- Algebraic Multigrid (AMG)-based Mesh Coarsening that preserves the geometry
- Mesh-size independent architecture by shared blocks



Previous state u^t Next state u^t

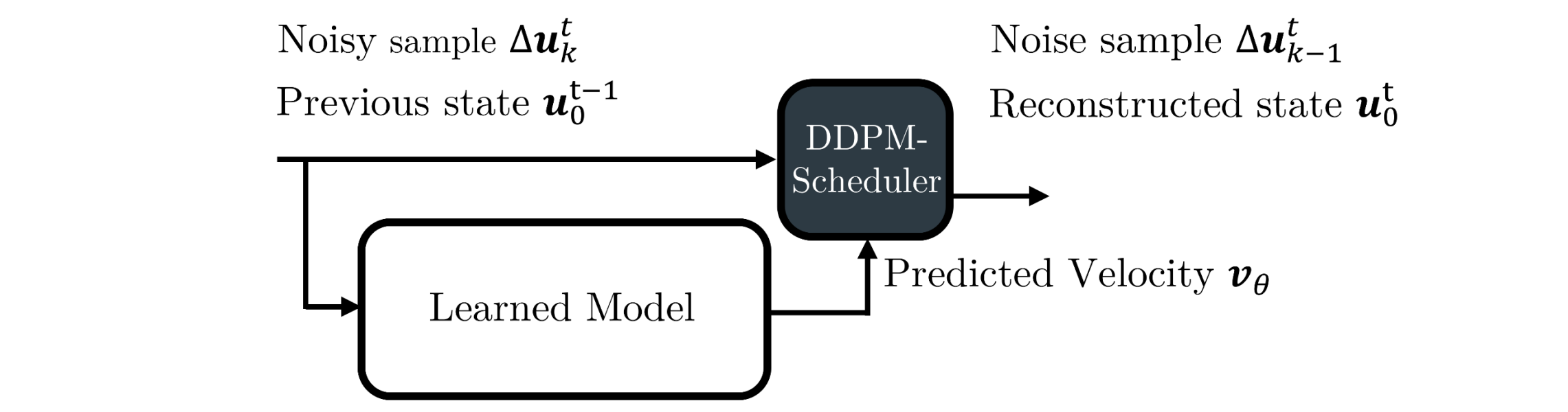
Mesh Coarsening

Algebraic MPN

Intra-Level-Message Passing Stack Inter-Level-Message Passing Stack

Denoising diffusion probabilistic models

- DDPMs and AMPNs allow for rich, high-fidelity predictions across frequencies
- Early denoising steps focus on global frequencies, and the later on local frequencies



Noisy sample Δu_k^t Previous state u_0^{t-1}

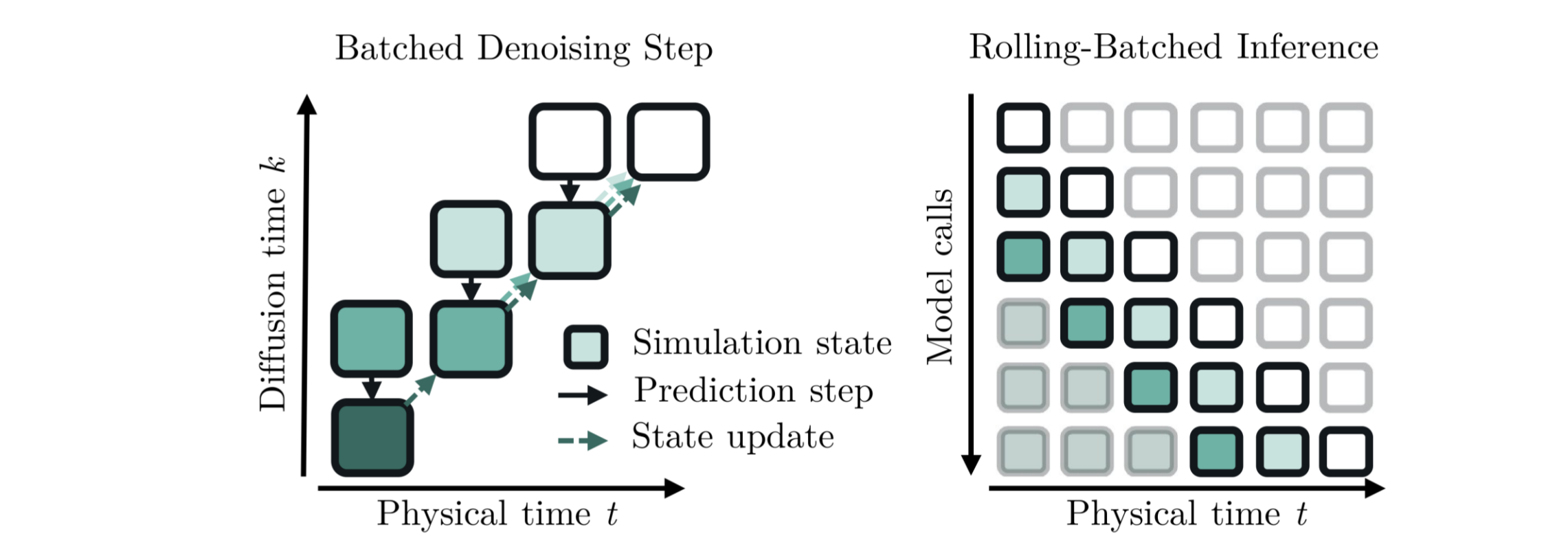
DDPM-Scheduler

Noise sample Δu_{k-1}^t Reconstructed state u_0^t

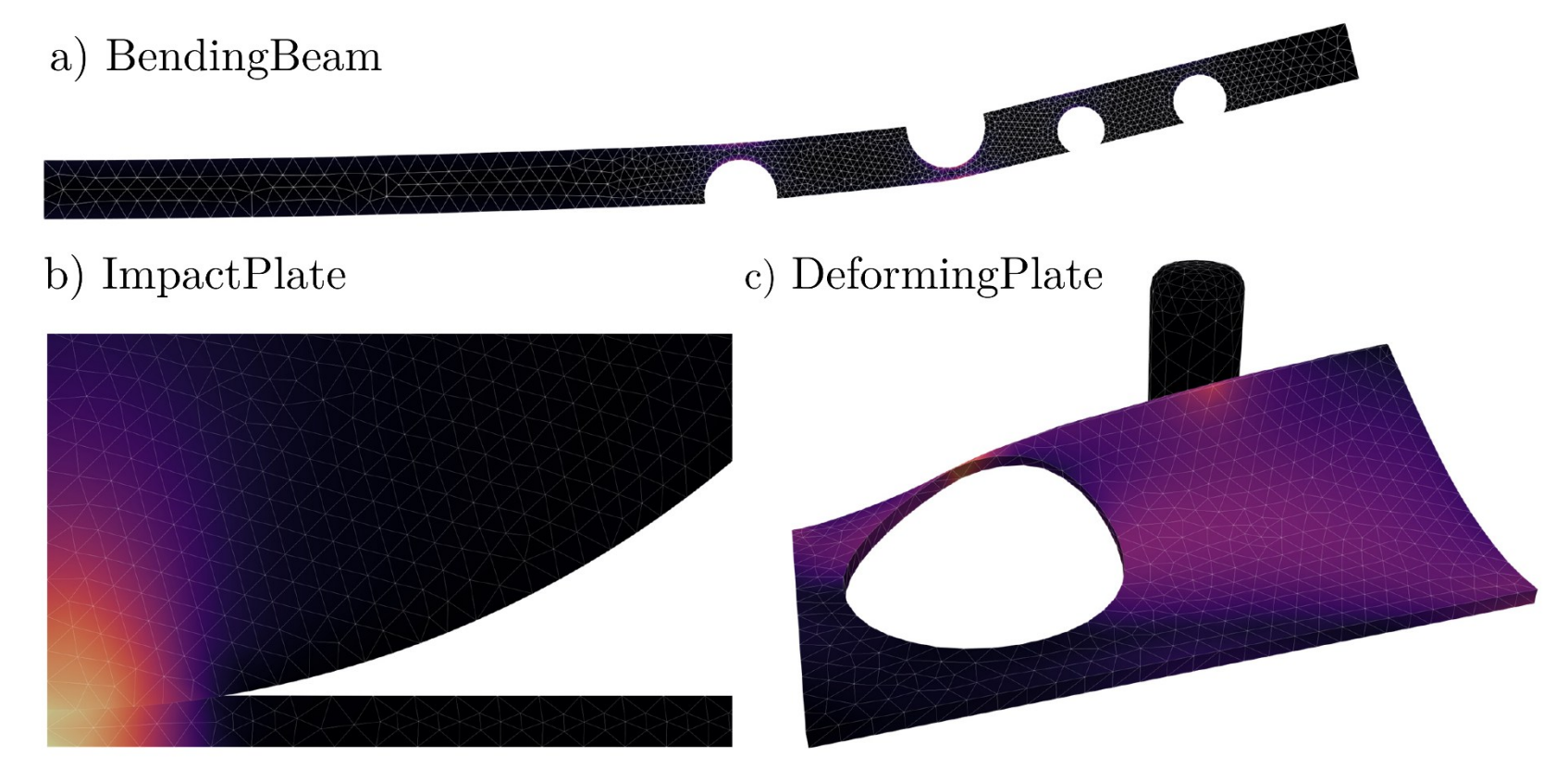
Learned Model Predicted Velocity v_θ

ROBI: Rolling diffusion-Batched Inference

- ROBI parallelize the denoising of consecutive time steps → $\approx \sigma(T)$
- The model prediction still only depends on the previous physical state, preserving training efficiency and time-shift equivariance
- Denoising stride and truncation step enable the trade-off of accuracy for speed




Datasets



Tobias Würth^{1*}, Niklas Freymuth²,
Gerhard Neumann², Luise Kärger¹

¹Institute of Vehicle System Technology
²Autonomous Learning Robots
*tobias.wuerth@kit.edu



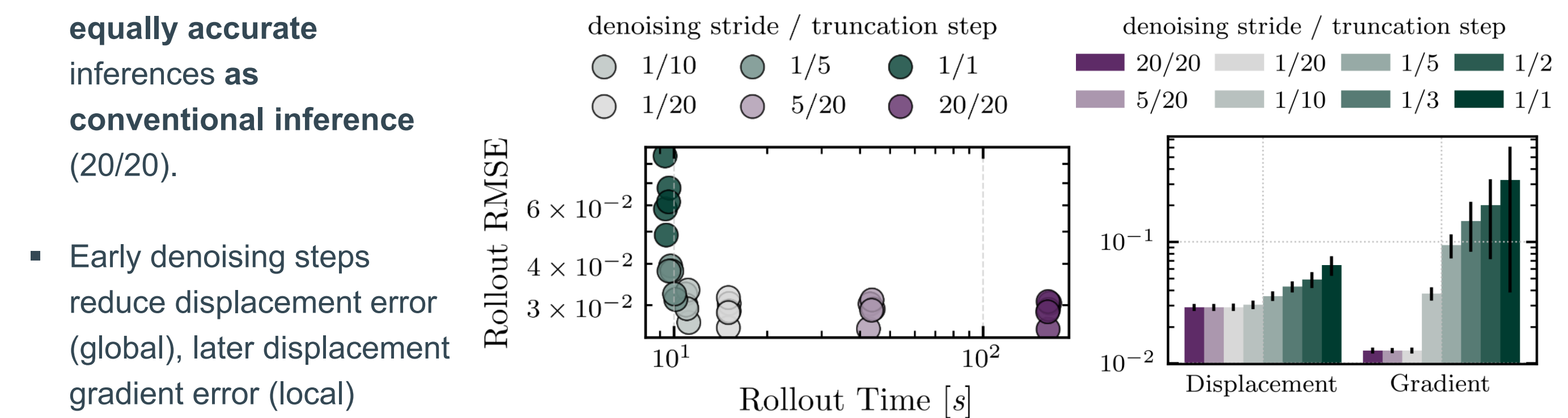
Results

High-fidelity physical simulations



Variable Inference with ROBI

- ROBI enables faster yet equally accurate inferences as conventional inference (20/20).
- Early denoising steps reduce displacement error (global), later displacement gradient error (local)



denoising stride / truncation step

1/10 1/5 1/1 20/20 1/20 1/5 1/2 5/20 1/10 1/3 1/1

Rollout RMSE

Rollout Time [s]

Displacement Gradient

Generalization to large meshes

- The AMPN architecture enables quick transfers to much larger meshes

