Proceedings of the 1st international Symposium on AI and Fluid Mechanics
Abstract No S2 A2

Deep Koopman Sensing

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Abstract

Inferring flow fields from noisy and sparse measurements is a critical challenge in fluid dynamics, with applications ranging from weather forecasting to biomedical engineering. Data assimilation (DA) has emerged as an effective framework for bridging numerical models with noisy and sparse observations. Traditional data assimilation approaches have relied heavily on numerical solvers, which require prior knowledge of the problem, the solver, and substantial computational resources. Although recent advances in deep learning have introduced faster alternatives, such as autoregressive nonlinear reduced-order models (ROMs) within the data assimilation (DA) pipeline, the inherent temporal nonlinearity of classical autoregressive nonlinear ROMs (e.g., CNN-LSTM) can introduce additional challenges for data assimilation. To address these challenges, we propose Deep Koopman Sensing, which combines a deep parametric Koopman-based ROM with data assimilation. During the offline phase, a deep parametric Koopman-based ROM is developed by lifting the high-dimensional state vector of the discretized PDE onto a latent space, where the temporal evolution of the lifted state is approximately linear. During the online phase, the trained ROM will be used to infer the full flow field from the streaming data of the sparse measurements. We validate the proposed framework across five benchmark problems: the 1D viscous Burgers equation, the 1D Kuramoto–Sivashinsky equation, the 2D Navier–Stokes flow past a cylinder, the 2D dam-break flow, and the 3D flow over a sphere. Our results demonstrate significant improvements in reconstruction accuracy compared to DMD and other deep learning autoregressive models.

Keywords:

Machine Learning, Data assimilation, Koopman Operator