Lario, Andrea; Maulik, Romit; Schmidt, Oliver T.; Rozza, Gianluigi; Mengaldo, Gianmarco
Neural-network learning of SPOD latent dynamics. (English) [Zbl 07578895]
J. Comput. Phys. 468, Article ID 11475, 21 p. (2022)

Summary: We aim to reconstruct the latent space dynamics of high dimensional, quasi-stationary systems using model order reduction via the spectral proper orthogonal decomposition (SPOD). The proposed method is based on three fundamental steps: in the first, once that the mean flow field has been subtracted from the realizations (also referred to as snapshots), we compress the data from a high-dimensional representation to a lower dimensional one by constructing the SPOD latent space; in the second, we build the time-dependent coefficients by projecting the snapshots containing the fluctuations onto the SPOD basis and we learn their evolution in time with the aid of recurrent neural networks; in the third, we reconstruct the high-dimensional data from the learnt lower-dimensional representation. The proposed method is demonstrated on two different test cases, namely, a compressible jet flow, and a geophysical problem known as the Madden-Julian Oscillation. An extensive comparison between SPOD and the equivalent POD-based counterpart is provided and differences between the two approaches are highlighted. The numerical results suggest that the proposed model is able to provide low rank predictions of complex statistically stationary data and to provide insights into the evolution of phenomena characterized by specific range of frequencies. The comparison between POD and SPOD surrogate strategies highlights the need for further work on the characterization of the interplay of error between data reduction techniques and neural network forecasts.

MSC:
76Fxx Turbulence
65Lxx Numerical methods for ordinary differential equations
82Cxx Time-dependent statistical mechanics (dynamic and nonequilibrium)

Keywords:
dynamical systems; reduced order modeling; neural networks; deep learning

Full Text: DOI

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