Nodycon2023
Data-driven Nonlinear Normal Modal Identification and Reduced-order Modeling: A Physics-integrated Deep Learning Approach

Shanwu Li* and Yongchao Yang*

*Department of Mechanical Engineering – Engineering Mechanics, Michigan Technological University, Houghton, MI, USA

Abstract. Identifying the characteristic coordinates or modes of nonlinear dynamical systems is critical for understanding, analysis, and reduced-order modeling of the underlying complex dynamics. While normal modal transformation exactly characterizes any linear systems, there exists no such a general mathematical framework for nonlinear dynamical systems. Nonlinear normal modes (NNMs) are natural generalization of the normal modal transformation for nonlinear systems; however, existing research for identifying NNMs has relied on theoretical derivation or numerical computation from the closed-form equation of the system, which is usually unknown. We present a data-driven method with physics-integrated deep learning for identifying NNMs and reconstructing the NNM-spanned reduced-order models of unknown nonlinear dynamical systems using response data only. We leverage the modeling capacity of deep neural networks with integration of physics knowledge about nonlinear dynamics to identify the forward and inverse nonlinear modal transformations and the associated modal dynamics evolution. We discuss the performance and applicability of the method on different nonlinear systems with comparisons with existing methods.

Introduction

Dynamical systems generally exhibit complex nonlinear phenomena, such as frequency-energy dependence and modal interaction. Their accurate modeling and representation typically require high-dimensional models, resulting in great difficulties in analysis and computations. Reduced-order modeling (ROM) aims to alleviate such modeling and computation challenges by identifying reduced-order models (ROMs) that accurately capture the dynamics embedded in the original high-dimensional space. While the proper orthogonal decomposition (POD) method has been successfully applied in ROMs with the advantage of computational efficiency thanks to its simplicity, its linear nature reduces its performance when handling intrinsically nonlinear dynamical systems. Nonlinear normal modes (NNMs), defined as invariant manifolds [1] in the state space, are natural bases that span a nonlinear subspace with clear physical interpretations. Furthermore, the generalized invariance property of NNMs allows finding the lowest-dimensional subspaces that capture the nonlinear dynamics. We present our recent study on developing a physics-integrated deep learning approach to discover ROM from measurement data only; it simultaneously identifies the NNMs-spanned subspace with a hierarchical order and the associated nonlinear modal dynamics. Specifically, our approach consists of 1) a hierarchical autoencoderthat identifies the nonlinear modal transformation function of NNM with a hierarchical order which indicates the relative contribution of each NNM to the observed responses; and 2) a dynamics-coder that identifies the evolution function of the NNM coordinates.

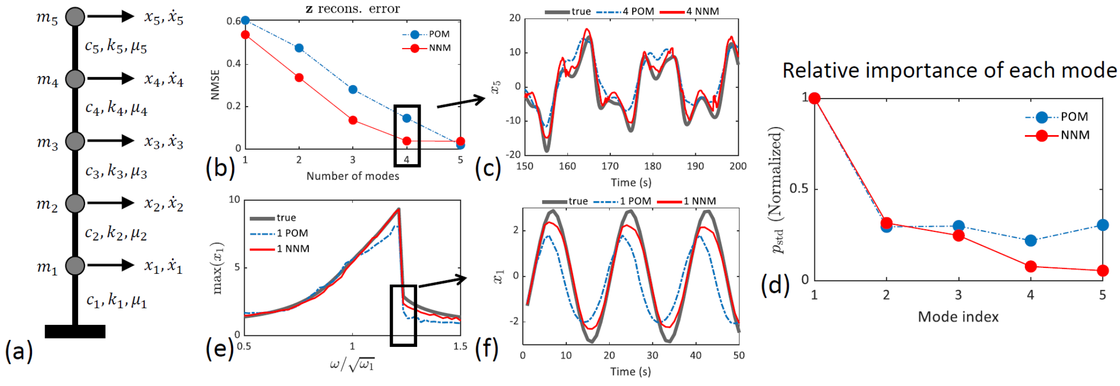

Figure 1: Numerical experiments on a nonlinear shear-type 5DOF system and the identification results.

Results and discussion

Reconstructions using identified NNM coordinates have smaller error than that by POD mode (POM) coordinates. Same conclusion can be drawn from the predicted time histories of states by 4-order ROMs based on POMs and NNMs. The oscillation amplitudes of transformed response that reveal relative importance of each identified mode for the observed response are shown in (d). For forced nonlinear systems, it is seen in (e) that the NNM-based ROM identified by our approach shows higher accuracy than POM-based ROM, especially in the vicinity of bifurcation frequency where the nonlinearity of the system is prominent.

References

[1] Shaw, S. W., and Pierre, C. 1993. Normal Modes for Non-Linear Vibratory Systems. Journal of Sound and Vibration, 164(1):85–124.