MS 09

Data-driven reduced-order Modeling of nonlinear dynamical systems

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Reduced-order modeling is among the leading theoretical and computational challenges for nonlinear systems in mechanics, ranging from structures and fluid flows, to their interaction and other multi-physics problems. Direct extraction of nonlinear footprint-frequency responses, bifurcations, nonlinear interactions, state transitions, non-trivial attractors, turbulence in such complex, high-dimensional models are computationally demanding, if not unattainable. Both in numerics or experiments, data-driven reduction constitutes an effective approach to obtain tractable models that capture nonlinear dynamics. These models should be orders of magnitude faster to solve in comparison to the full system, as well as accurate. Moreover, reduced-order models are not only used for understanding system behavior, but they would also enable design optimization and efficient controllability. Data-driven model reduction methods are well-established for linear dynamical systems. For small deviations from equilibria, the fundamental tool is modal analysis, both numerical and experimental. Linear tools, such as proper orthogonal decomposition or dynamics mode decomposition, also extend to dynamics near other simple attractors, such as limit cycles, but they would ultimately be incapable of handling truly nonlinear behavior, which is ubiquitous in mechanics. In this context, available nonlinear data-driven approaches tend to be sensitive in identified parameters and to be limited in their predictive power. For example, the addition of forcing terms or perturbation of parameters reveals to be unbearable, especially for black-box models. Another challenge is that of handling extremely high dimensional data coming from numerical simulations, such as those of commercial finite element codes or DNS solvers. Therefore, recent developments are trying to blend high-performance techniques from machine learning with physical principles, so that identified models would be more amenable to scientists and practitioners in terms of generalization and predictive capabilities.

With this proposal, we stimulate submissions on recent developments on data-driven model reduction or identification of nonlinear dynamical systems, either using data from numerical simulations, experimental measurements or both. In the case of numerical simulations, model reduction methods should be substantially based on solvers data, augmented with some eventual prior information (e.g., linear modes and their dynamics). We welcome contributions proposing new methods and/or applications (e.g., identification, control) in specific problems concerning various fields of mechanics such as mechanical structures, fluid dynamics, fluid-structure interaction and eventually also other multi-disciplinary areas. This mini-symposium aims at discussing techniques and case studies that go beyond matching training and testing data, with the goal of providing accurate and meaningful results in capturing essentially nonlinear phenomena.