Assessing the performance of Data-based and Physics-based Model Order Reduction techniques for Geometrically nonlinear problems

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ABSTRACT

Despite many advancements in computational resources, the cost of using them for simulating high-fidelity (Finite Element) models is still high. Model order reduction aims to reduce this by projecting the entire system of equations onto a lower-dimensional subspace through a projection function. In this contribution, we look at two ways of generating these projection functions, data-based and physics-based approaches. In the data-based method, called Proper Orthogonal Decomposition (POD) [1, 2], Singular Value Decomposition (SVD) is applied to a training data set (generated from varying parameters of the same high-fidelity problem) to obtain the projection function. For the physics-based approach, named Linear Manifold (LM), the dynamic eigenmodes of the system are extended using modal derivatives that can capture the effect of nonlinear kinematics. These so-called modal derivatives and dynamic eigenmodes form the projection function [3, 4]. In this contribution, we intend to model quasi-statics of the same high-fidelity problem (that can be extrapolated to dynamics, if necessary) to observe the difference between these methods. To this extent, we propose a residual parameter in the reduced space for both these methods and an additional mode selection algorithm for the physics-based method (LM). As a start, we assess the performance of both these methods on problems involving geometric nonlinearity. The results showed that the displacement error for these methods for model problems involving simple loading scenarios falls way below 1% and a computational time gain of approximately $25 - 30\%$ compared to the original FE calculation. The difference in these methods has been visible in complex loading scenarios, where LM takes less number of modes compared to POD to reach an error below 1%, but the time gain remains the same.

References

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