Inducing System Structure in Data-driven Approaches to Model Reduction

Christopher Beattie
Virginia Tech/TU-Berlin
beattie@vt.edu

Abstract

The simulation of complex systems that span multiple time and space scales while incorporating multiphysics has become a standard tool for design and optimization. The dynamics of such processes are commonly modeled through coupled dynamical systems, which can be analyzed and then used in deriving optimization and control strategies. The cost for tasks associated with simulation and analysis of such systems typically grows superlinearly with model order, so there is incentive to replace the original system (or signficant subsystems) with low-order, high-fidelity surrogate models. Model-order reduction techniques such as rational Krylov methods and balanced truncation are popular tools to create such reduced-order models, yet they generally require a standard state-space representation of the dynamical system which even when possible, usually obscures system structure. Conversely there are interpolatory model reduction approaches that permit retention of system structure (e.g., second-order structure, delay system structure, or passivity). In some settings there are great benefits that accrue from deriving reduced models directly from measured data - often from frequency-domain system response measurements. These 'data-driven' approaches are nonintrusive to the extent that access to internal system structure is not necessary, however they produce reduced models as standard first order realizations so that any underlying system structure is inevitably lost. I will discuss a fairly general approach to structure-preserving data-driven model reduction that reconciles these two different frameworks and for the most part combines their advantages.

References

1. P. Schulze and B. Unger and C. Beattie and S. Gugercin. Structure-preserving data-driven model reduction. TU-Berlin preprint (2015).