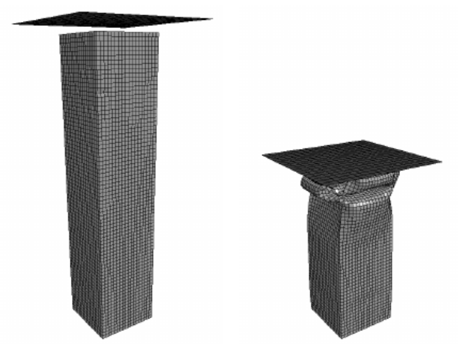
FG Computational Mechanics

Software Lab:

Modeling: ★★★★☆
Mathematics: ★★★★★
Programming: ★★★★☆
Science: ★★★★★

Reduced basis adaptivity for model order reduction

Setting



Nonlinear model order reduction aims at reducing the computation times of numerical simulations (e.g. FEM, CFD). This is done by expressing the solution in terms of a small number of global, generalized coordinates related to "empirical modes" rather than the high number of DOF of the original model. This is done using a reduced basis matrix [**V**], extracted from a set of training simulations.

In many scenarios, it is desirable to adapt the reduced basis to new physical phenomena which the existing empirical modes cannot represent to a sufficient level of accuracy. Further, the residual, which can be measured in the reduced simulation, has been shown to be often correlated to the true error. To this end, we would like to extend an existing Python-based reduced-order 1D Burgers' equation solver with the capability to adapt the reduced basis according to the residual in the reduced simulation, following approaches in literature [2,3]. The methods can be extended to FEM or CFD.

Task

Extend an existing Python solver such that:

- it can solve the dynamic Burgers' problem [1] using reduced basis adaptivity [2, 4]
- the adaptive methods work well together with hyper-reduction, e.g. DEIM [4]
- it enables users to visualize the results, possibly in an interactive manner

Supervisors

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References

[1] Amsallem, D., Zahr, M. J., & Farhat, C. (2012). Nonlinear Model Order Reduction Based on Local Reduced-Order Bases. International Journal for Numerical Methods in Engineering, 92(10), 891–916.

[2] Carlberg, K. (2015). Adaptive h-refinement for reduced-order models. International Journal for Numerical Methods in Engineering, 102(5), 1192–1210.

[3] Peherstorfer, B., & Willcox, K. (2015). Online Adaptive Model Reduction for Nonlinear Systems via Low-Rank Updates. SIAM Journal on Scientific Computing, 37(4), A2123–A2150.

[4] Chaturantabut, S., & Sorensen, D. C. (2010). Nonlinear Model Reduction via Discrete Empirical Interpolation. *SIAM Journal on Scientific Computing*, *32*(5), 2737–2764.