Oral presentation | Reduced order models

Reduced order models-I

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[1-C-03] Reduced Order Model-based Uncertainty Analysis for Fluid-Structure Interaction Problems

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Reduced-Order Model-based Uncertainty Analysis for Fluid-Structure Interaction Problems

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1 Introduction

Fluid-Structure Interaction (FSI) problems are common in various engineering fields, such as aerospace, marine engineering, civil engineering, and biomedical engineering. However, the accurate simulation and prediction of these problems pose a significant challenge due to inherent uncertainties, including uncertain material properties, measurement errors, model parameters, initial and boundary conditions, and numerical approximations. Therefore, it is crucial to accurately understand and quantify the uncertainties inherent in FSI problems. Traditional high-fidelity models used in FSI analysis are typically resource-intensive and time-consuming, making them impractical for extensive uncertainty analysis. As an alternative, non-intrusive reduced-order modeling (ROM) becomes a potential solution. Inspired by Sun *et al.* [1], we propose a non-intrusive reduced-order model based on tensor train decomposition (TTD) [2] and polynomial chaos expansion (PCE). The proposed ROM is used to perform an comprehensive uncertainty quantification (UQ) analysis for various FSI problems.

2 Numerical method: TTD-PCE

An approximation of the random field $u(x,t,\xi)$, which is dependent on space, time, and random parameter, can be represented using a combination of TTD and PCE as follows:

$$u(x,t,\xi) \approx \sum_{l=1}^{L} \sum_{k=0}^{P-1} c_l^k \Phi^k(\xi)\psi_l(x,t). \quad (1)$$

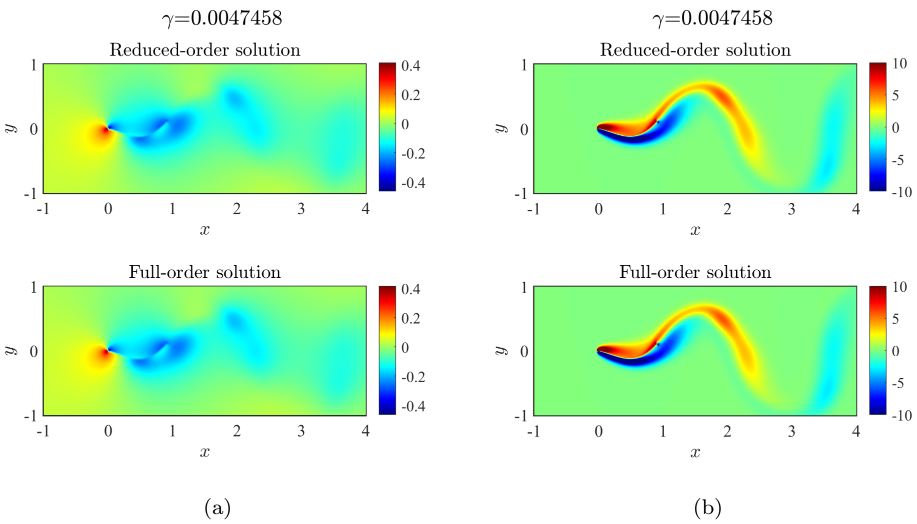

Figure 1: Comparison between reduced order solutions and full-order solutions at $t = 29.6$: (a) pressure; (b) vorticity.

3 Numerical results and discussions

3.1 Validation of TTD-PCE

We considered a flapping flexible fin fixed in a certain position, where the full order solutions are obtained using the monolithic immersed boundary projection method [3]. Figure 1 shows the comparison between the reduced-order and full-order solutions. Both the pressure and vorticity show good agreement, which validates the effectiveness and accuracy of the proposed TTD-PCE.

3.2 Parameter identification

Parameter identification is crucial in the study of FSI problems, providing insights into complicated factors that influence their dynamics. Bayesian inference offers us a method to infer parameters by considering their probability distributions. We considered an observation of the time-averaged leading velcoity of the flapping fin for $\gamma = 0.02$. The Bayesian inference yielded a Maximum A Posteriori (MAP) estimation of $\gamma = 0.058$. Despite the discrepancy, the identical time-averaged leading velocity at both 0.058 and 0.02 indicated a model calibration process. This highlights the capability of our framework to provide accurate predictions even when the estimated parameter deviates from the reference value.

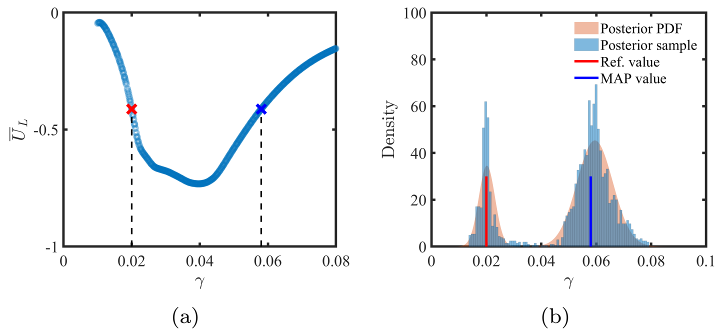

Figure 2: Parameter identification and its posterior distribution for the bending rigidity: (a) observation; (b) pdf of γ.

4 Conclusions

We proposed a ROM based on TTD and PCE, which was validated through various benchmark and FSI problems, demonstrating its accuracy and efficiency. Furthermore, the parameter identification illustrates that the proposed ROM serves not only as a calibration function but also provides valuable insights for inverse problems related to FSI problems.

Acknowlement

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