PROPOSITION DE SUJET DE THÈSE

Intitulé : Model Predictive Control based on domain decomposed reduced order models with adaptive hyper-reduction

Référence : **MFE-DAAA-2024-13**

(à rappeler dans toute correspondance)

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Mots clés

Flow control, Model reduction, CFD

Profil et compétences recherchées

Présentation du projet doctoral, contexte et objectif

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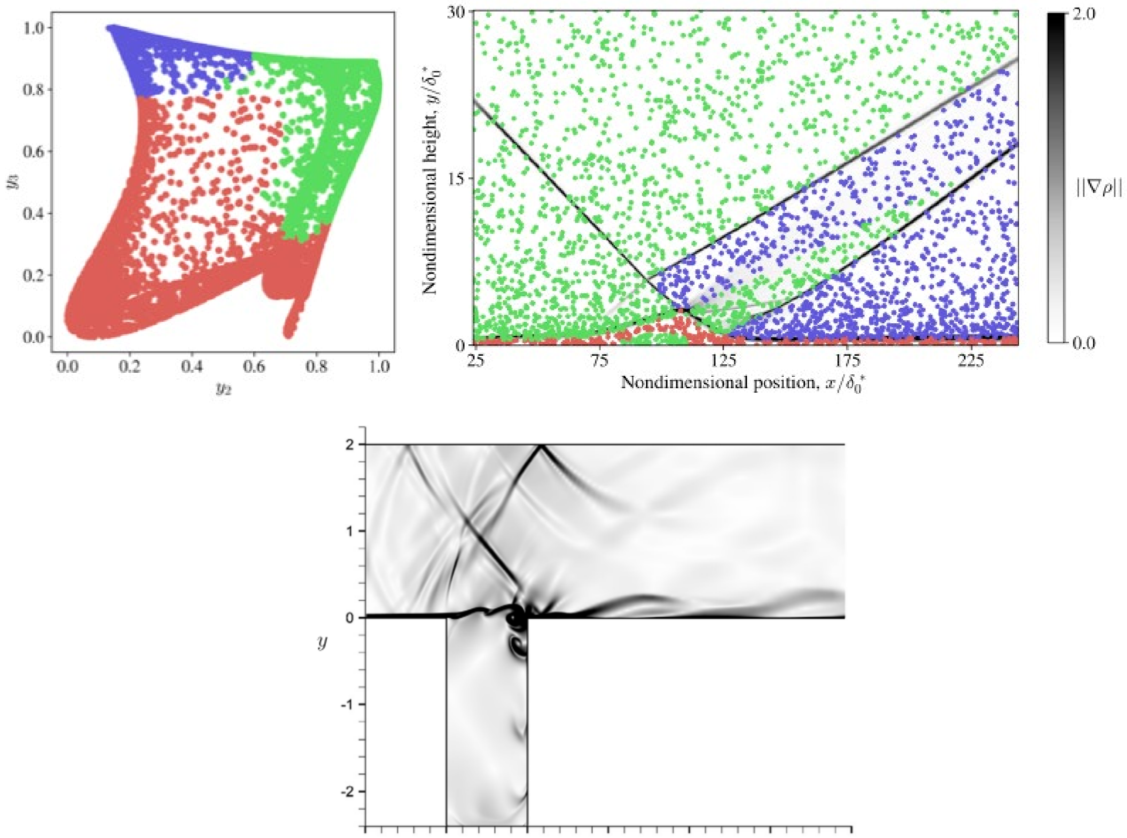

(b)

Figure1: (a) Clustering of dynamics in shock-BL-interaction Ma = 5.95 [Sherding], (b) pseudo-Schlieren of subsonic cavity flow (2D URANS) [Mettot].

High-fidelity simulations of unsteady and complex flows, while predictive, are very costly due to the multiple time and length scales present in the calculations. In multi-query applications, such as model predictive control, unsteady and high-fidelity simulations (full-order models) become quickly inapplicable due to this high cost of function evaluations.

Reduced-order models (ROM)s can be used to represent approximate but cheap models of the full system (FOM), **allowing for fast prototyping and multiple queries.** However, to be applicable, ROMs, which are commonly inferred using non-intrusive data-driven techniques, **need to be robust and predictive**. This requirement is not guaranteed, when applied to time-evolving (i.e. ***dynamical***) data. In this context, ROMs have proven to be unreliable in reconstructing long-time behavior of the analytical system, and **lack robustness to changes in operating conditions or input parameters** (i.e. generalisability). Recent studies [Duraisamy,Sherding] have shown that, integrating adaptivity in the reductive process, can improve predictability and generalisability of the models, making them applicable in the context of optimisation and control.

The objective of this thesis is to apply model predictive control (MPC) to reduced-models that are learned on the fly by projecting the Navier-Stokes equations on a POD basis that evolves adaptively due to new states that are encountered as control is applied. We consider as a first step the case of full-state-measurement, in which the current state is assumed to be known at all times (data-assimilation techniques could be leveraged in future work to adapt the methodology to the case of partial-state-measurements). The current sub-space (or manifold) can therefore be obtained and adapted through incremental SVD techniques [Singler] while the reduced-order model can be derived by hyper-reduction techniques [Farhat] and efficiently modified on the fly [Duraisamy]. To enhance the efficiency of the reduced-order-model, a physics-informed clustering of the spatial domain (see figure 1a; [Costanzo]) can be additionally employed to obtain low-order approximations of the flow state in a number of dynamically distinct sub-domains. An approximation of the flow in the full domain can then be handled by a domain decomposition technique to fit the ensemble of local representations [Iollo].

With respect to reinforcement learning techniques, the present approach has the advantage of incorporating models obtained by physical governing equations and should therefore be more accurate and robust to extrapolation. This feature allows the overall algorithm to be quicker in finding the descent path toward the control objective. Several parameters are at hand to tune the accuracy of the models: number of sub-domains, size of adaptive reduced basis in each sub-domain, number of points used in the hyper-reduction technique to enforce the residuals of the Navier-Stokes equations to be zero, correction or closure-term that can in principle be added to match past and current observations in the case where the reduced-order model only captures part of the frequency content of the model.

Finally, considering that the model may only be an approximation of the true dynamics, transfer learning techniques [Wang, Humbrid] will be investigated to fine-tune the reduced-order model to actual high-fidelity measurements.

We will apply the methodology to cases of increasing complexity:

- stabilization of 2D incompressible open cavity-flow at Re=7500 with a model consisting of 2D incompressible Navier-Stokes equations.
- stabilization of subsonic open-cavity flow with data obtained from 2.5D LES simulation and model obtained by projecting a 2D URANS model (see figure 1b).

References:

- [Singler] Fareed, H., Singler, J. R., Zhang, Y., & Shen, J. (2018). Incremental proper orthogonal decomposition for PDE simulation data. Computers & Mathematics with Applications, 75(6), 1942-1960.
- [Farhat] Farhat, C., Chapman, T., & Avery, P. (2015). Structure-preserving, stability, and accuracy properties of the energy-conserving sampling and weighting method for the hyper reduction of nonlinear finite element dynamic models. International journal for numerical methods in engineering, 102(5), 1077-1110.
- [Duraisamy] Huang, C., & Duraisamy, K. (2023). Predictive reduced order modeling of chaotic multi-scale problems using adaptively sampled projections. arXiv preprint arXiv:2301.09006.
- [Iollo] Riffaud, S., Bergmann, M., Farhat, C., Grimberg, S., & Iollo, A. (2021). The DGDD method for reduced-order modeling of conservation laws. Journal of Computational Physics, 437, 110336.
- [Costanzo] Costanzo, S. (2022). Numerical methods for control and optimisation of fluid flows (Doctoral dissertation, Sorbonne Université).
- [Wang] Z. Wang *et al.* (2023). A general deep transfer learning framework for predicting the flow field of airfoils with small data, Computers & Fluids, 251.
- [Humbrid] K. D. Humbird, J. L. Peterson, B. K. Spears and R. G. McClarren (2020). Transfer Learning to Model Inertial Confinement Fusion Experiments, *IEEE Transactions on Plasma Science*, 48 (1): 61-70.

Collaborations envisagées

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