∂'Alembert Institute

Internship proposal in Computational Fluid Mechanics

Development of efficient Reduced Order Models for the Navier-Stokes equations using Deep-Learning

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Reducing a detailed system into smaller sized models, capable of reproducing the main features and dynamics of the original configuration is a common practice in optimisation and control community, which could also serve as a way to make function evaluations less expensive. Since control is one of the future applications of this study it is necessary to identify the most suitable methodology applicable to detailed Navier-Stokes simulations for prediction purposes (Fig. **??**).

To this end various strategies such as the GNAT method (Gauss-Newton with approximate tensors [1]) and the conventional POD-DEIM methods [2] can be considered to derive efficient reduced order models in the context of an incompressible Navier-Stokes solver with immersed boundaries. In the present intership, a particular attention will be paid to improve these models by considering the recently proposed POD with Galerkin regression method SINDy, implemented with machine learning algorithm [2]. Alternatives based on deep-learning approaches will also be studied.

The capability of these methods to interpolate between various operating conditions and to extrapolate the solution will be investigated. The ability of each reduction strategy in dealing with existing nonlinearities and moving immersed boundaries will be also identified.

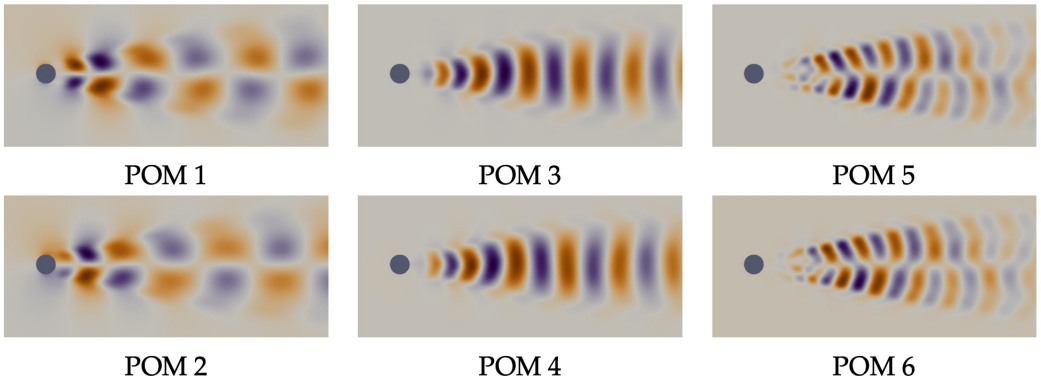

FIGURE 1 – Density field of the first 6th Proper Orthogonal Modes (POM) for the unsteady flow past a circular cylinder at $Re = 100$.

References

[1] K. Carlberg, M. Barone, and H. Antil, Galerkin v. least-squares Petrov- Galerkin projection in nonlinear model reduction, Journal of Computational Physics, vol. 330, pp. 693–734, 2017.

[2] S. Chaturantabut and D. C. Sorensen, Nonlinear Model Reduction via Discrete Empirical Interpolation, SIAM Journal on Scientific Computing, vol. 32, no. 5, pp. 2737–2764, 2010.

[3] J-C Loiseau, S.L. Brunton. Constrained sparse Galerkin regression, Journal of Fluid Mechanics, 838 (42-47), 2018