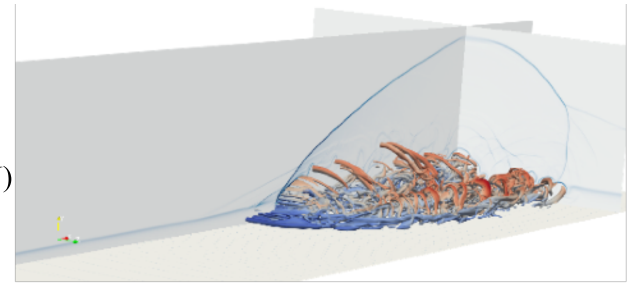
PHysics-based Learning for robUst fluid SIMulation (ANR porject: PHLUSIM)

Type of offer :
Ph.D.



Location :
Mathematical and Numerical Modelling Laboratory (M2N)
Applied Mathematics & Statistics Department (EPN6)
Conservatoire Nationale Arts et Métiers (le CNAM)
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Context :
The massive reliance on computational fluid dynamics (CFD) for research and engineering has led to the creation of massive and ever-growing fluid dynamics databases. These are significantly under-leveraged by historically low-dimensional approaches. The parallel with recent trends in AI, which point to learning techniques that improve by exploiting very large datasets using high-dimensional formulations, suggests that large gains can be made by overcoming these limitations. These alternative methods improve the extraction of essential and relevant information and significantly improve modeling approaches. Many data-driven fluid models have started to include a large number of *local* variables, meaning the road to higher dimensionality now lies with *context-aware* strategies, which can learn to automatically extract relevant information about the surrounding flow state and domain topology to refine their predictions. In this project, we explore the benefits and challenges provided by using context-aware learning techniques to extract predictive reduced-order model (ROM)s.

In the context of flow simulations, ROMs represent approximate but cheap models of a physical phenomenon, allowing for fast prototyping and multiple queries. Model order reduction consists of restricting the search of a solution to a low-dimensional space spanned by a reduced-order basis. The latter is inferred from a set of precomputed high-fidelity solutions commonly using linear dimensionality reduction techniques, such as proper-orthogonal decomposition (i.e. principal component analysis), dynamic mode decomposition, etc. Despite important progress, most state-of-the-art ROMs fail to demonstrate robustness to uncertainties while remaining predictive when highly unsteady and turbulent systems are concerned. The main drawback in most reduction techniques is that reduced bases are learned using linear dimensionality reduction techniques and do not properly handle nonlinear problems which are commonplace in complex flow configurations. Recently, making use of recent advances in neural network architecture, nonlinear dimentionality reduction techniques have been infused in ROM community, using autoencoders and Convolutional (CNN) and Graph (GNN) neural networks.

However, novel approaches examine using mesh-free approaches, such as coordinate-based NNs to learn basis functions directly from the continuous vector field itself and not from its discretization while dynamics are modeled in a latent space. This hyper-reduction approach is discretization-independent and features lower memory consumption than prior discretization-dependent ROM approaches be they linear (PODs) or nonlinear (auto-encoders). In the same spirit, neural operators, which allow learning discretization-free representations, can be explored to build ROMs. These mesh-free methods will be explored in this project.

Profile :
The candidate should have a MSc degree or equivalent in fluid mechanics or applied mathematics, with experience in scientific computing.

Skills :
Programming experience and expertise in data-driven techniques will be considered very positively.

Duration and start date :
The position is offered for the duration of 36 months, between October 1st, 2024 and September 30th, 2027. **Deadline for applications: 31/05/2024**

Required documents :
The applicant should include a CV, and a motivation letter.

Contacts :
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References :
[1] Johannes Brandstetter, Daniel E. Worrall, and Max Welling. "Message Passing Neural PDE Solvers". In: *International Conference on Learning Representations*. 2022. url: https://openreview.net/forum?id=vSix3HPYKSU.
[2] Rizal Fathony, Anit Kumar Sahu, Devin Willmott, and J Zico Kolter. "Multiplicative filter networks". In: *International Conference on Learning Representations*. 2021.
[3] Vincent Sitzmann, Julien Martel, Alexander Bergman, David Lindell, and Gordon Wetzstein. "Implicit neural repre- sentations with periodic activation functions". In: *Advances in Neural Information Processing Systems* 33 (2020), pp. 7462–7473.
[4] Peter Yichen Chen *et al*. "CROM: Continuous Reduced-Order Modeling of PDEs Using Implicit Neural Representations". In: *ICLR 2023*. 2022. url: http://arxiv.org/abs/2206.02607.
[5] Zongyi Li et al. "Fourier Neural Operator for Parametric Partial Differential Equations". In: *ICLR*. 2021.
[6] C. Scherding, G. Rigas, D. Sipp, P.J. Schmid, and T. Sayadi, Ronaalp: Reduced-order nonlinear approximation with active learning procedure, 2023.
[7] C. Scherding, G. Rigas, D. Sipp, P. J. Schmid, and T. Sayadi, Data-driven framework for input/output lookup tables reduction: Application to hypersonic flows in chemical nonequilibrium, *Phys. Rev. Fluids*, 8 (2023), p.023201
[8] S. Kneer, T. Sayadi, D. Sipp, P. Schmid, and G. Rigas, Symmetry-aware autoencoders: s-pca and s-nlpca, *arXiv*, (2021), p. 2111.02893v2