PhD in fluid mechanics

Turbulent convection: numerical modelling and physics-enhanced machine learning, Laboratoire LISN, Orsay (France)

Supervising team
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Summary
At very high Rayleigh numbers, a very intense heat transfer regime appears for which the triggering mechanisms are still poorly understood. Using HPC numerical simulations and physics-guided machine learning techniques, we seek to extract from data physical information bringing to light the multi-scale interactions between different turbulent flow structures.

Context

The Rayleigh-Benard convection is established in a cavity under the effect of a temperature difference imposed on the horizontal walls, the bottom wall being heated. The resulting flow in the turbulent regime is a multi-structured and multi-scale phenomenon characterized by the superposition of small-scale plumes (heat vectors), a large-scale mean flow filling the cavity, boundary layers and turbulent fluctuations.

For many years, we have been simulating this physical phenomenon by direct numerical simulation (DNS). The transition to massively parallel simulations now allows us to consider calculations at parameter levels close to experiments. However, these calculations are very heavy and even if the spatio-temporal description of the flow can be very fine, it is difficult to approach statistically all the scales of the flow, to store all the computed fields, or to easily replay the sequences.

Despite progress made by careful comparison of experimental and numerical simulations studies, key differences remain in the amount and nature of the information provided by each community, making conjoint understanding difficult. For instance, experimental data is incomplete (probes time series, 2D fields sequences or images), but well converged and can reach high forcings. Numerical simulations are fully resolved in space, but reach lower turbulence level and for shorter durations. The tremendous potential capabilities of recent physics-informed deep learning (DL) techniques will help in seamlessly integrating the benefits of each approach into a new modeling and comprehension of turbulent physics.

In this project, we will take advantage of both perceptrons or (graph) convolutional neural networks frameworks enhanced with physical constraints, in order to mitigate the risks and to speed up and robustify the training phase of the models. More specifically, objectives are to infer missing data from experiments, and alleviate the cost of expensive numerical simulations by reducing the storage cost.

Methodology

The project seeks to take advantage of the capabilities of machine learning techniques to reduce the complexity of the data. These techniques will be deployed at the interface between numerical models and solvers, and experimentally acquired data, not only to facilitate comparison, but also to access unmeasured/unquantifiable information in terms of variables or resolution finesse, and to guide physical exploration.

Two types of architecture will be considered based on deep or graph convolution neural networks, in which physical constraints enrich the output data for an accelerated convergence, with two distinct objectives. First, it is about processing multi-source experimental data acquisition to reconstruct hidden quantities fields, and test ideas about the super-resolution reconstruction to improve the spatial resolution of measures. Second, it is to extract physical informations from experimental images. DNS data are used for preliminary tests, but also provide additional information, leading to mixing of experimental and numerical databases.

Several encouraging internships have already been carried out on the topic [Lucor et al. JCP 2022]. A large DNS database already exists [Belkadi et al. JFM 2021], but it will be expanded as needed using the resources of GENCI's national supercomputers. The project will focus on hidden scalar or field variables reconstruction and/or superresolution using DNS or / and experimental data, useful to better understand physical couplings between simultaneous flow quantities.
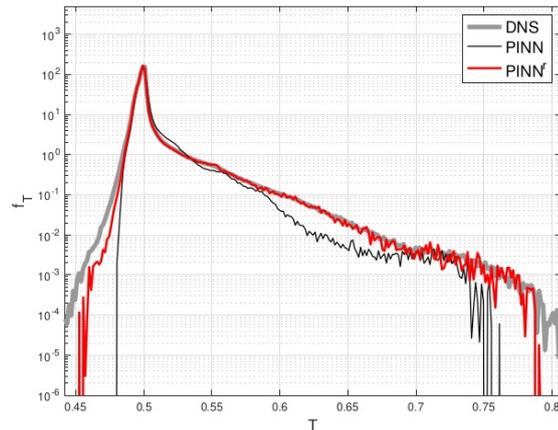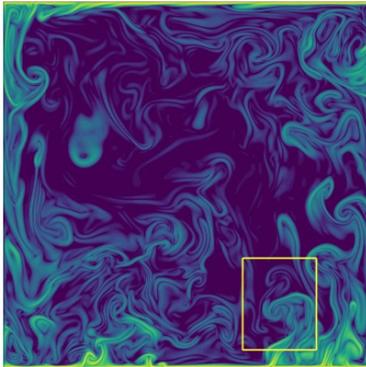
PINN predictive capabilities for Rayleigh-Bénard flow at Ra=2.10^9 [LAS22]. Left: Example of instantaneous heat dissipation field in a 2D slice from 3D DNS. The domain over which the PINN model is trained, is depicted as a transparent box. Right: probability density function of the temperature fluctuations within the training domain. The reference PDF is computed from the full DNS while the two PINNs PDF are evaluated on the predicted test sample.

Expected profile

- Master of Science or equivalent in applied mathematics, physics, or mechanical engineering, with competences in fluid dynamics, statistics, or scientific computing
- Good programming skills, especially in Python programming
- Good writing skills

Contact and application procedure

For further information, please contact:
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Please send preferably before *May 15, 2022,* a detailed CV, a cover letter, letters of recommendation if any and a transcript of higher education records (at Master level)

References

[Bel+ 2021] Belkadi, M., Sergent, A. Fraigneau, F. and Podvin, B. On the role of roughness valleys in turbulent Rayleigh-Bénard convection. J. Fluid Mech. 923, A6, (2021).
[LAS22] D Lucor, A Agrawal, A Sergent, Simple computational strategies for more effective physics-informed neural networks modeling of turbulent natural convection. J. Comp. Phys. 456 (2022). hal-03159996, p. 111022.