

PDE-CONSTRAINED NEURAL NETWORK FOR TURBULENT RAYLEIGH-B ÉNARD CONVECTION

Atul Agrawal, Didier Lucor, Yann Fraigneau, Berengere Podvin, Anne Sergent

► To cite this version:

Atul Agrawal, Didier Lucor, Yann Fraigneau, Berengere Podvin, Anne Sergent. PDE-CONSTRAINED NEURAL NETWORK FOR TURBULENT RAYLEIGH-B ÉNARD CONVEC-TION. European Numerical Mathematics and Advanced Applications Conference (ENUMATH2019), Sep 2019, Egmond aan Zee, Netherlands. hal-04400942

HAL Id: hal-04400942 https://hal.science/hal-04400942

Submitted on 17 Jan2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

PDE-CONSTRAINED NEURAL NETWORK FOR TURBULENT RAYLEIGH-BÉNARD CONVECTION

A. Agrawal¹, D. Lucor¹, Y. Fraigneau¹, B. Podvin¹, and A. Sergent^{1,2}

¹LIMSI, CNRS, Universit Paris-Saclay, Campus universitaire bât 508 Rue John von Neumann, F - 91405 Orsay cedex, France, didier.lucor@limsi.fr ²Sorbonne Université, UFR dIngénierie, F-75005, Paris, France

Abstract

The motivation of this work stems from the limited understanding of the physical mechanisms responsible for the heat transfer enhancement in rough turbulent Rayleigh-Bénard convection. Indeed, strong dynamic interactions between a large spatial/time scale range from mean wind to small-scale plumes remain difficult to comprehend with a single numerical or experimental emulator [1]. The development of data-driven surrogate models for the prediction of complex physical phenomena, in place of more standard numerical simulations, is an ongoing challenge in various fields and may help for this particular application [2, 3]. Here, we decide to rely on deep neural networks (DNN) which are known to be performant in capturing transient and intermittent phenomenon with the possibility of handling translations, rotations and other invariances. More specifically, the approach retained in this project is the one of training a DNN based on a cost function that involves a set of partial differential equations (PDEs). The idea is to incorporate prior scientific knowledge to be used as a guideline for designing efficient deep learning models [4, 5]. In particular, a reasonable approach is to incorporate (some of) the governing equations of the physical model (e.g. mass/momentum/energy conservation) at the core of the DNN, i.e. in the loss/likelihood functions. We propose to investigate how this additional information effectively regularizes the minimization procedure in the training of DNN, and enables them to generalize well with fewer training samples. More specifically, we will report on the influence of the choice of the domain of interest for data acquisition as well as subsequent training and predictions, in relation to the problem geometry and initial/boundary conditions. Finally, we will report on the DNNs training attempt on large direct numerical simulations database acquired for turbulent convective flow in rectangular cavity with rough bottom plate.

REFERENCES

- [1] E. Rusaouën, O. Liot, B. Castaing, J. Salort, and F. Chillà. Thermal transfer in Rayleigh-Bénard cell with smooth or rough boundaries. *J Fluid Mech.*, (837):443–460, 2018.
- [2] B. Podvin and A. Sergent. Precursor for wind reversal in a square Rayleigh-Bénard cell *Physical Review E* 95(1), 013112, 2017.
- [3] J.N. Kutz. Deep learning in fluid dynamics. J Fluid Mech., 814:14, 2017.
- [4] M. Raissi, P. Perdikaris, and G.E. Karniadakis. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J. Comp. Phys., 378:686707, 2019.
- [5] Y. Zhu, N. Zabaras, P. Koutsourelakis, and P. Perdikaris. Physics-constrained deep learning for high-dimensional surrogate modeling and uncertainty quantification without labeled data. *arXiv*:1901.06314, 2019.