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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.

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