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Addressing turbulent convection experimental data challenges in PINNs with appropriate physical sampling

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Numerical and experimental approaches are becoming more complementary approaches to address highly turbulent regimes thanks to improvements in computation resources. Nonetheless, experimental results, such as meshless 3D3C Particle Tracking Velocimetry, are often spatially sparse, somewhat discontinuous, subject to measurement noise and incomplete, while CFD simulations still require intensive resources to solve all the time scales. To address these issues, we employ Physics Informed Neural Networks (PINNs) [2], which provide a meshless way to enrich and complement experimental data [1]. In the case of turbulent convection, our framework allows 3D temperature discovery, denoising, and generating continuous field representations [3]. Departing from the idealized case of Eulerian training-reconstruction, we propose a spatio-temporal sampling framework to tailor our DNS database to closely resemble experimental measurements. This poses additional challenges to PINNs particularly on addressing spatial gaps, tracking loss and scarcity of experimental-type labels. An important question arises on the optimal choice of collocation points to help alleviating these constraints. Our analysis focuses on the impact of PDE collocation points density through parallel GPU computations. Additionally, we explore the effectiveness of smart adaptive spatial PDE sampling to mitigate information loss with respect to relevant turbulent quantities caused by inherently noisy and sparse data.

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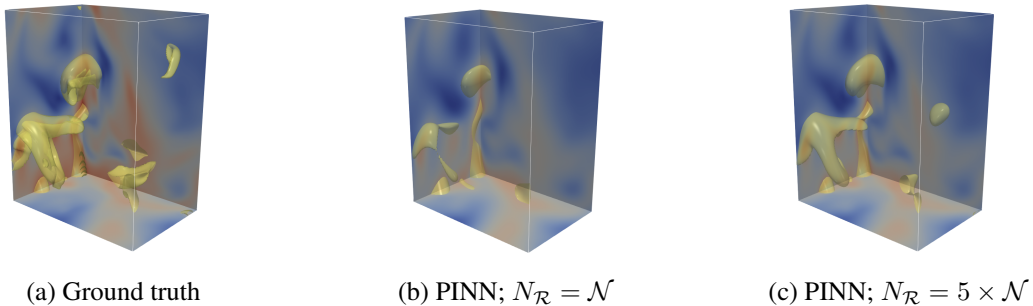


Figure 1: 3D-Reconstruction of instantaneous turbulent convection field ($Ra = 2 \times 10^9$, $Pr = 4.4$) from experimental-like data at iso-budget of labels. $N_{\mathcal{R}}$ is the total number of PDE collocation points. Iso-surfaces of temperature and velocity magnitude at the boundaries with the same ground truth colorbar.

References

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