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Inferring Temperature Fields in the PIV Measurement Plane from Two-Component Velocity Data using PINNs: Case Rayleigh-Bénard Convection

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Abstract: Recent studies revealed the capabilities of physics-informed neural networks (PINNs) to predict instantaneous temperature fields in turbulent convective flows using three-dimensional (3D) velocity fields [6, 4]. Inferring the temperature in thermally-driven flows is highly relevant in various technical applications that require precise analysis and control of heat transfer, such as the design of interior ventilation systems in aircraft or train cabins, to optimize air circulation and ensure thermal comfort [1]. As 3D velocity measurements are still demanding in terms of equipment, we investigate whether relying onto two-dimensional (2D) measurements only is feasible. A classical experimental technique is particle image velocimetry (PIV), which, in its simplest form, provides planar fields of the two in-plane velocity components. While PINNs have already shown great potential for improving the quality of PIV measurements [2], in this study, we challenge the PINN approach to reconstruct temperature fields using only planar two-component velocity data within a cubic Rayleigh-Bénard Convection (RBC) cell.

Leveraging available direct numerical simulation data at $\mathrm{Ra} = 10^7$ and $\mathrm{Pr} = 0.7$ enables the direct validation of the PINN-predicted fields. The PINN loss formulation typically has the following main contributions: a data loss term and loss terms incorporating the residuals of the governing partial differential equations and the boundary conditions [5]. To address the lack of information perpendicular to the PIV plane, we minimise the residuals in an enclosing 3D domain $\mathcal{D}$, as motivated in [3], together with weighted dynamic sampling strategies. The thickness δ_x of $\mathcal{D}$ has to be chosen carefully within $0 < \delta_x \leq H$ depending on the characteristic flow length scales. Since only the two in-plane velocity components are available, the PINN has considerable freedom when reconstructing the orientation of the out-of-plane velocity component. Consequently, it is necessary to include additional constraints to account for the global in-plane mass conservation.

Current results of the temperature predictions show encouraging results with a Pearson Correlation Coefficient $\rho_T = 0.92$ (fig. 1 right). As we have only partial knowledge of the 3D velocity field, guiding the PINN towards the global minimum is more difficult. Therefore, a challenge in this work is developing an effective strategy for handling the additional physical constraints.

Our method serves as a foundation for future research focused on inferring temperature fields through in-field measurements in industrial applications. To demonstrate its applicability, we will apply it to real PIV data and compare the results with temperature fields measured via Particle Image Thermometry (PIT).

Keywords: Physics-informed Neural Networks, Rayleigh-Bénard Convection, PIV

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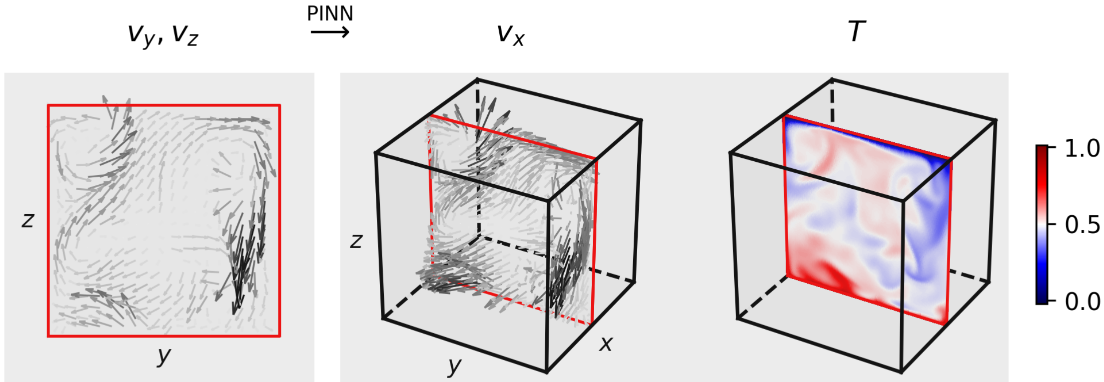

Figure 1: Schematic of a cubic RBC cell with height H for the test case $\mathrm{Ra} = 10^7$ and $\mathrm{Pr} = 0.7$. We train a PINN with the two in-field velocity components on the vertical plane $A : x = 0.5\,H$ (left) and by minimising the residuals of the PDEs within a 3D collocation layer around A to obtain the out-of-plane velocity component (middle) and the temperature field (exemplary result on the right).

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