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Physics-constrained multi-fidelity convolutional neural networks for surrogate fluid modeling LUNING SUN, JIAN-XUN WANG, University of Notre Dame — Deep neural networks (DNN) have attracted increasing attention in surrogate modeling of fluid dynamics due to their strong expressivity and fast online inference speeds. In general, the performance of DNN-based models largely relies on a representative training set of high-fidelity (HF) data (from high-fidelity simulations or experiments), which, however, are too expensive to obtain sufficiently. On the other hand, low-fidelity (LF) data, although less accurate, often can be produced in a large amount with low costs. In this work, we develop a physics-informed multi-fidelity transfer learning strategy that leverages both HF and LF labeled information to effectively parameterize solutions of fluid flows in high dimensional parameter space. Moreover, PDE-based physics knowledge is incorporated into the training process to enforce learned solutions to conform to physical laws. The effectiveness of the proposed method is demonstrated on several canonical problems with transport phenomena, governed by classic PDEs, e.g., convection-diffusion equations and Navier-Stokes equations.

Luning Sun
University of Notre Dame

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