# Convolutional feature-enhanced physics-informed neural networks for reconstructing two-phase flows

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## Abstract:

Two-phase flow phenomena play a crucial role in various engineering applications, including hydrogen fuel cells, spray cooling techniques, and chemical reactors. Specialized optical measurement techniques, such as shadowgraphy and particle image velocimetry can reveal the gas-liquid interface evolution and internal velocity fields, respectively. However, these experiments are largely limited to planar observations and further restricted by narrow optical access, whereas the flow dynamics are inherently three-dimensional (3D). To address this issue, we propose a novel convolutional feature-enhanced PINNs framework, designed for the spatio-temporal reconstruction of two-phase flows from single-view planar measurements obtained by color-coded shadowgraphy. Deep learning techniques based on convolutional neural networks (CNNs) provide a powerful approach for the volumetric reconstruction of the flow field based on experimental data by leveraging the spatial structure in the images and extracting context-rich features. Building on this foundation, Physics-informed neural networks (PINNs) offer a complementary and promising alternative by integrating prior knowledge in the form of governing equations into the network's training process. By combining the strengths of both approaches, this integration enables accurate predictions even with limited data. The developed PINNs encode the single-field, two-phase formulation of the Navier-Stokes equations and the advection equation for the phase indicator while training on the results of highly resolved direct numerical simulation (DNS). The proposed approach is first validated on synthetic data generated through DNS, demonstrating high spatial accuracy in reconstructing the three-dimensional gas-liquid interface, along with the inferred velocity and pressure fields. We further apply this framework to reconstruct the dynamics of an impinging droplet from planar experimental data, demonstrating the practical applicability and significant potential of the proposed approach to real-world fluid dynamics analysis. In the conference contribution, we extend our analysis to additional two-phase flow phenomena, including rising bubbles, demonstrating the adaptability of the proposed approach.