COFTEC Research Seminar

From Images to Hidden Flow Fields: CFD-Guided Machine Learning for Two-Phase Flow Reconstruction

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@Graduate School of Engineering, Kobe University
Lecture room TBA 17:00-

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Multiphase Flows with Heat Transfer
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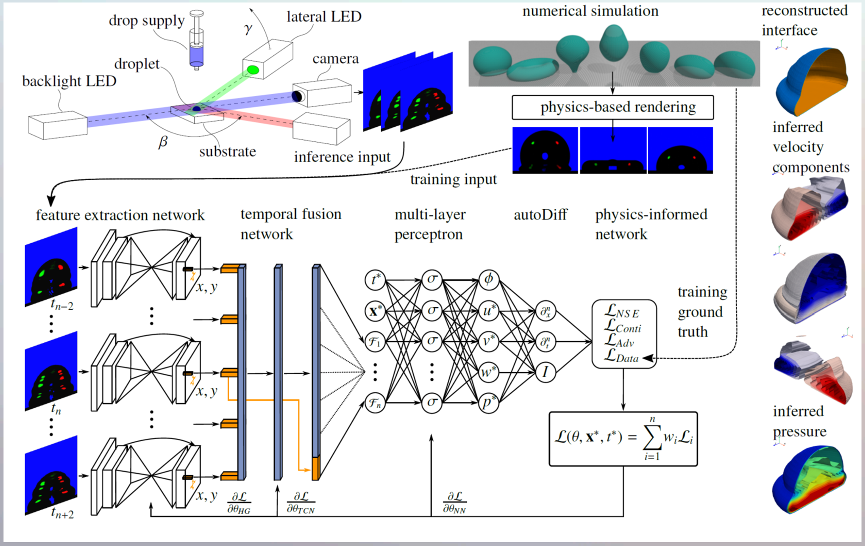
Two-phase flows are governed by dynamic gas–liquid interfaces whose shape, motion and internal flow topology control processes such as spray cooling, coating, inkjet printing and fuel-cell operation. Conventional optical diagnostics provide valuable experimental access, but standard shadowgraphy mainly delivers two-dimensional projections of inherently three-dimensional interface dynamics. Measurements of internal droplet flow are even more difficult, because refraction at the curved interface distorts optical access. Numerical simulations can provide volumetric information, but they are expensive, case-specific and require experimental validation.

This talk presents a framework that combines experimental imaging, CFD and physics-informed machine learning to reconstruct hidden three-dimensional flow information from image sequences. The experimental basis is glare-point shadowgraphy: a blue backlight captures the droplet contour, while red and green lateral light sources create color-coded glare points on the gas–liquid interface. These glare points encode information about local interface orientation and out-of-plane deformation that is not available from the shadowgraph contour alone.

To decode this information, phase-field simulations of droplet impingement are combined with physics-based rendering to generate synthetic image sequences with known phase, velocity and pressure fields. These data are used to train PINNs4Drops, a video-conditioned physics-informed neural network framework. A convolutional feature extractor processes the images, a temporal network extracts spatio-temporal information, and a multilayer perceptron predicts the phase distribution, three velocity components and pressure field in continuous space and time. The reconstruction is constrained by both CFD data and the governing equations of incompressible two-phase flow.

The results show that physics-informed reconstruction improves the robustness and physical consistency of monocular droplet measurements. VoF-based PINNs improve out-of-plane reconstruction, temporal consistency, volume conservation and interface curvature compared with a purely data-driven baseline. Video-conditioned PINNs further infer continuous 3D velocity and pressure fields from image sequences with average validation errors of about 6–9%. Applied to real droplet-impact experiments, the method recovers physically plausible hidden flow topology from a single optical view.

Overall, this work illustrates a new route for experimental fluid mechanics: images are treated not only as direct measurements, but as information-rich observations that can be decoded by CFD-trained, physics-constrained machine learning to reveal fluid-dynamic quantities that are otherwise difficult or impossible to measure directly.



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