Physics-Informed LIF Inversion for Full-Field Temperature and Scalar Transport in Convective Jet Flows

Introduction

Quantitative temperature measurements using **Laser-Induced Fluorescence (LIF)** in convective flows commonly rely on multi-dye or multi-camera configurations to mitigate the effects of non-uniform illumination, dye concentration variations, and optical distortions. In many applied research environments, including Deltares, a Dutch knowledge institute, such experimental setups are impractical due to limitations in facilities, costs, or operational constraints. Accurate temperature characterization of buoyant jets and thermal plumes remains essential for environmental flow assessment and model validation. One relevant example is **aquathermia**, a low-carbon heating and cooling solution in which thermal discharge to surface water is constrained by the environmental impact of low-temperature effluent. Reliable laboratory-scale measurements are therefore required to understand plume dynamics, heat spreading and mixing, and to validate in-house developed numerical models. These models can then be applied by engineers to design renewable energy solutions that are both effective and environmentally sustainable.

Machine learning techniques, notably neural networks, enable the learning of complex patterns in data. A modern development is the incorporation of physical knowledge, in particular mathematical descriptions of physics in the form of loss functions based on differential equations, known as physics-informed machine learning, and in particular **physics-informed neural networks (PINNs)** [1,4,6]. These methods can be employed for both forward and inverse problems; in this project, we focus on the **inverse problem of flow reconstruction** from LIF measurements.

This project investigates whether physics-informed machine learning can be used to improve temperature reconstruction from constrained LIF measurements by explicitly enforcing the governing transport equations during the inversion process.

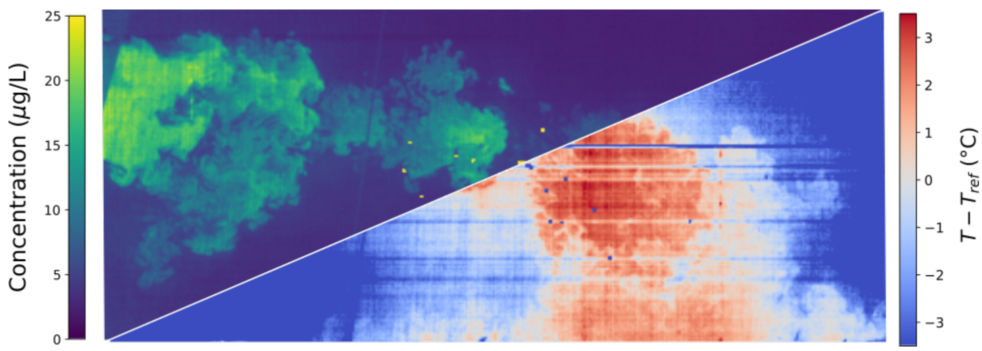

Figure 1 Example of LIF measurement providing concentration and temperature measurements from an image.

Objective

The objective of this MSc project is to evaluate the feasibility and accuracy of a **physics-informed approach**, for example using physics-informed neural networks (PINNs; [1,4,6]) or physics-informed neural operators (PINOs; see [5,7]), for reconstructing **full-field temperature distributions** from single-dye, single-camera **LIF data** in **convective flows**; neural operators extend neural networks from function approximation to mappings between function spaces.

The project is a **numerical feasibility** and **proof-of-concept** study, with the following goals:

- Develop a simplified numerical model of a two-dimensional (buoyant) jet, including a temperature advection–diffusion equation augmented with a forward model of the LIF signal that accounts for temperature dependence, dye concentration effects, and spatially varying illumination. This model will be used to **generate synthetic data for testing and validating the machine learning methodology.**
- **Implement a physics-informed inversion framework** that enforces the temperature transport equation during the reconstruction from synthetic LIF intensity data.
- Assess **reconstruction accuracy** and robustness relative to conventional per-pixel calibration methods under non-ideal measurement conditions.

The project does not aim to replace existing LIF calibration methods, but rather to investigate whether physics-informed machine learning can enhance current temperature reconstruction techniques in constrained measurement conditions.

Methodology

- Conduct a **literature review** of physics-informed approaches applied to inverse problems in experimental fluid mechanics and scalar transport.
- Develop a **numerical test case** of a buoyant jet by solving the temperature advection–diffusion equation.
- Generate **synthetic LIF intensity fields** using a simplified forward model that relates temperature and dye concentration to measured fluorescence.
- Implement a **physics-informed inversion framework** that reconstructs the temperature field from sparse or degraded LIF intensity data while enforcing the governing transport equation.
- Investigate the **ill-posedness of the inverse problem** and study the role of **regularization**, including both classical and physics-informed techniques, as well as potential algorithmic improvements in physics-informed machine learning.
- **Evaluate and validate** the reconstruction by comparing the results to reference temperature fields and to those obtained using conventional calibration approaches.

What do we expect?

- Background in fluid mechanics, partial differential equations (PDEs), and numerical methods for PDEs.
- Experience with machine learning, as well as implementation in Python (e.g., PyTorch and/or JAX).

Why join Deltares?

In addition to developing professionally with us with this challenging project, we also offer:

- An open, inclusive and collaborative culture.
- The opportunity to work with researchers from one of the knowledge institutes for applied research (TO2) in the Netherlands.

Contact

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