COMPLETE FLOW CHARACTERIZATION AND RECONSTRUCTION VIA PHYSICS-INFORMED NEURAL NETWORKS

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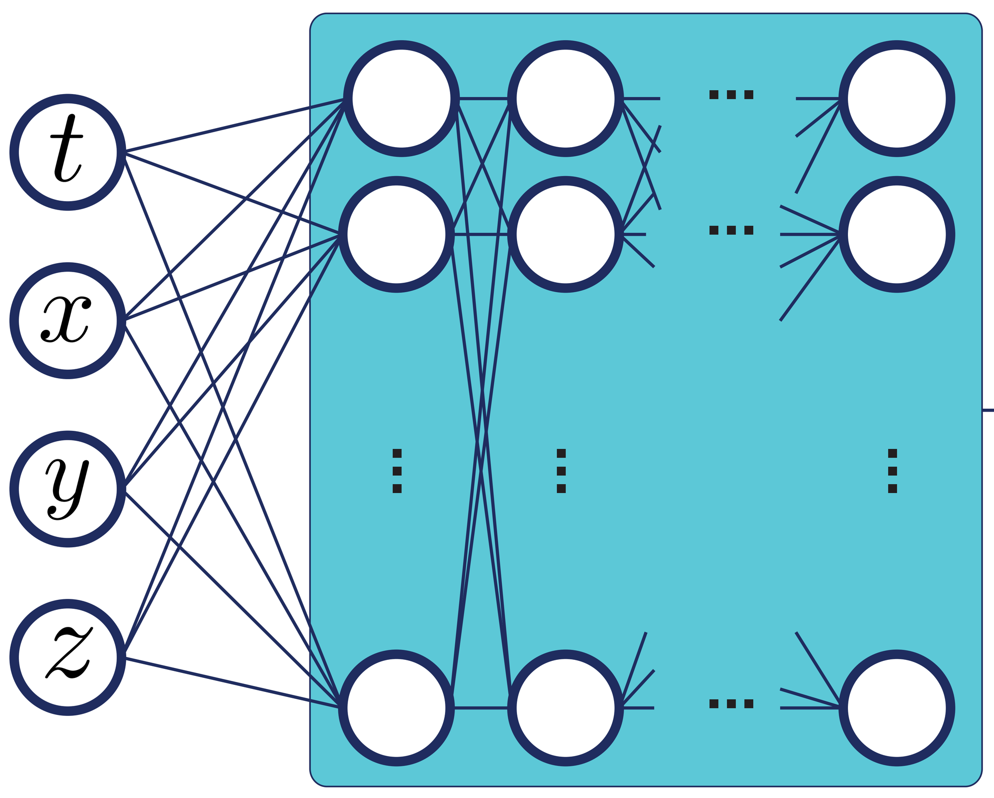
Abstract

Physics-Informed Neural Networks (PINNs) stand out as a recently introduced methodoly which allows for the reconstruction of field variables from incomplete measurements enforcing compliance with physics laws, e.g. Navier-Stokes equations for turbulent flows. Our research aims at developing a framework which enhances Particle Image Velocimetry (PIV) measurements using PINNs as a tool for data assimilation. Our optimized methodology adapts the data to the physics constraints in an iterative manner, and therefore, enables measuring additional flow quantities (e.g. pressure). Furthermore, it accounts for measurement errors by enforcing compliance with the Navier-Stokes equations. PINNs-PIV shows to be able to achieve a precise reconstruction of a full fluid domain on a desired grid which complies at all points with physics laws and with significant accuracy improvement.

Model architecture



Fully-connected layers

Loss function

Navier-Stokes equations

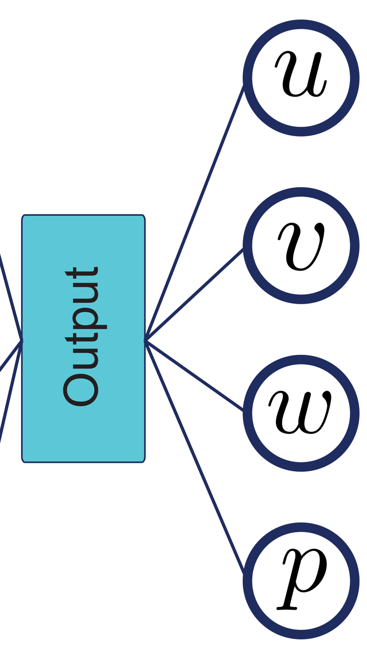
$$\begin{cases} \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0 \\ \frac{\partial u}{\partial t} + \left(u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} + w\frac{\partial u}{\partial z}\right) = -\frac{\partial p}{\partial x} + \frac{1}{Re}\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2}\right) \\ \frac{\partial v}{\partial t} + \left(u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} + w\frac{\partial v}{\partial z}\right) = -\frac{\partial p}{\partial y} + \frac{1}{Re}\left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} + \frac{\partial^2 v}{\partial z^2}\right) \\ \frac{\partial w}{\partial t} + \left(u\frac{\partial w}{\partial x} + v\frac{\partial w}{\partial y} + w\frac{\partial w}{\partial z}\right) = -\frac{\partial p}{\partial z} + \frac{1}{Re}\left(\frac{\partial^2 w}{\partial x^2} + \frac{\partial^2 w}{\partial y^2} + \frac{\partial^2 w}{\partial z^2}\right) \end{cases}$$

Reference velocities

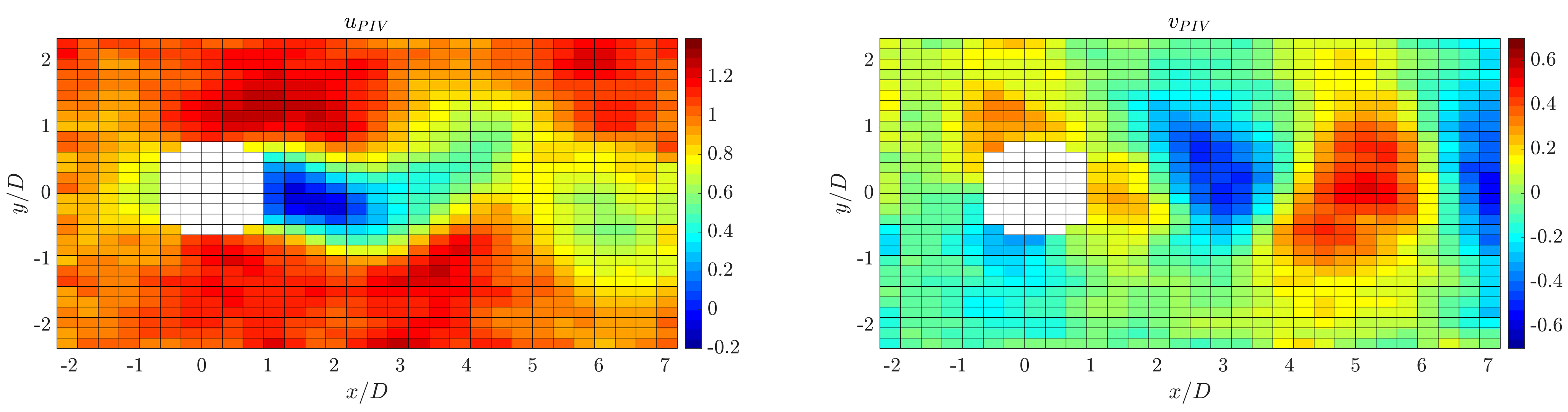
$$\begin{cases} u = u_{PIV} \\ v = v_{PIV} \quad \text{for points in PIV grid} \\ w = w_{PIV} \end{cases}$$

Inlet pressure

$p = p_{\text{inlet}}$ at inlet position



PIV (experimentally accessible) velocity field



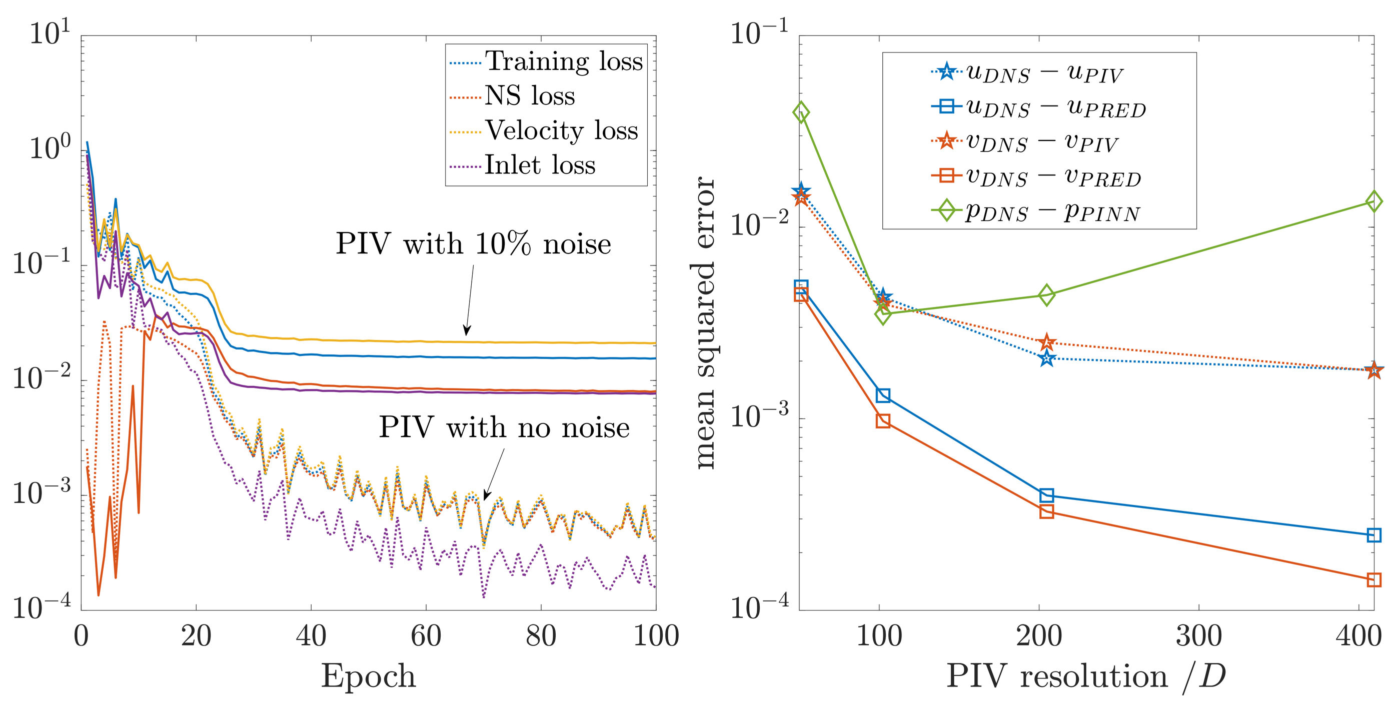
Physics-Informed Neural Network (PINN)

Error analysis

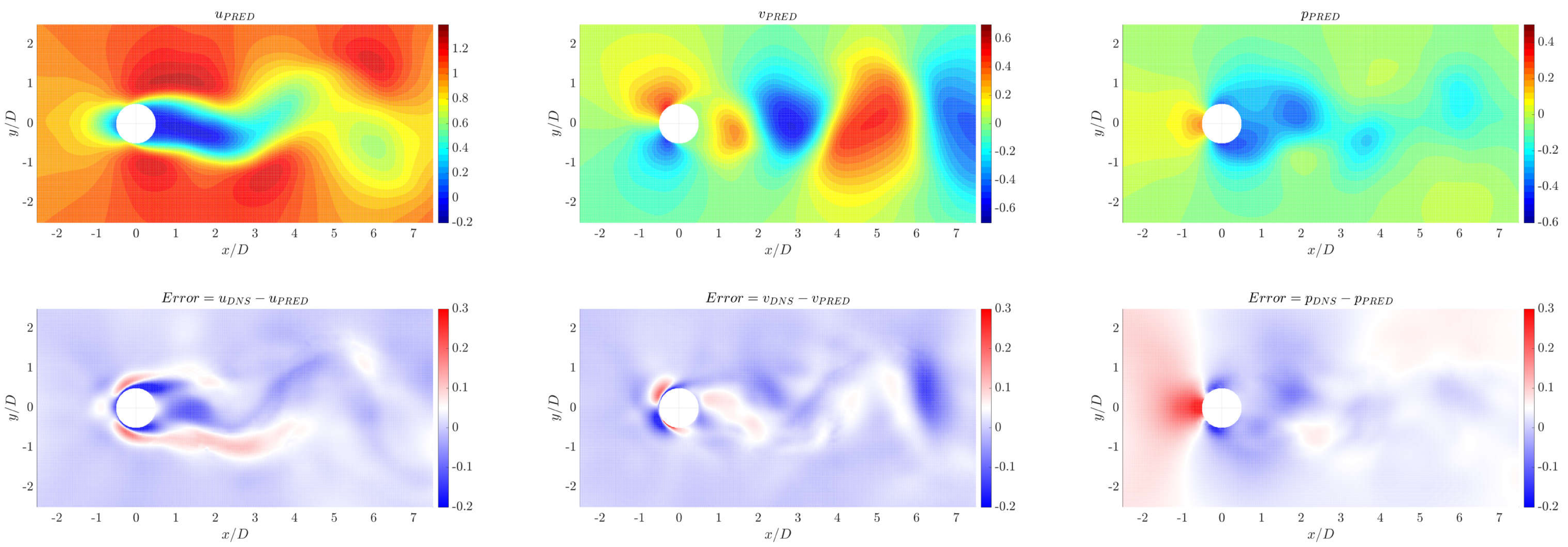
An adaptative loss function weights higher the contribution of error with higher value.The system becomes thus very robust and may correct noisy data from experiments

$$\mathcal{L} = w_{NS}\mathrm{L}_{NS} + w_{vel}\mathrm{L}_{vel} + w_{inlet}\mathrm{L}_{inlet}$$

$$\text{where } w_{\bullet} = \frac{\mathrm{L}_{\bullet}}{\mathrm{L}_{NS} + \mathrm{L}_{vel} + \mathrm{L}_{inlet}}$$



Reconstruction



Synthetic data from Direct Numerical Simulation are used as a reference for error calculation

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