Complete flow description from combination of incomplete measurements

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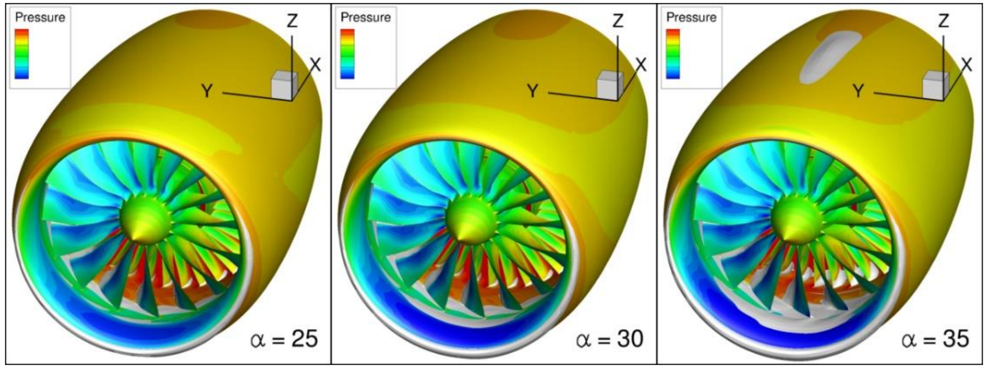
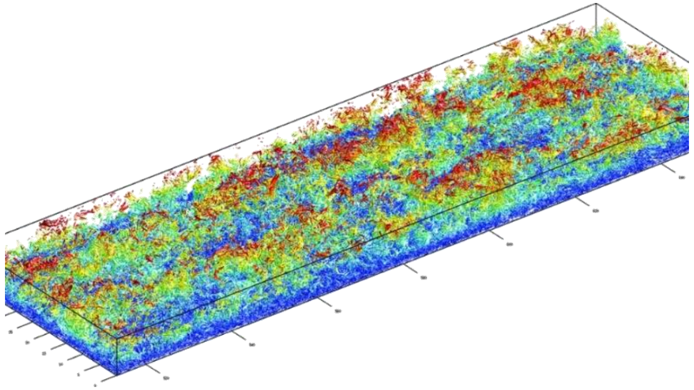
MOTIVATION



Aeroacoustics



Turbulence

Aerodynamic loads

- Time-resolved velocity and pressure fields are important in research and engineering

- Direct measurements of pressure are limited to point wise or surface measurements

figure from ONERA (up), University of Texas at Auston (downleft), and autosport (downright)

The pressure gradient can be computed from the Navier-Stokes (N-S) equation

$$\nabla p = -\rho \left(\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\mathbf{u} - \nu \Delta \mathbf{u} \right)$$

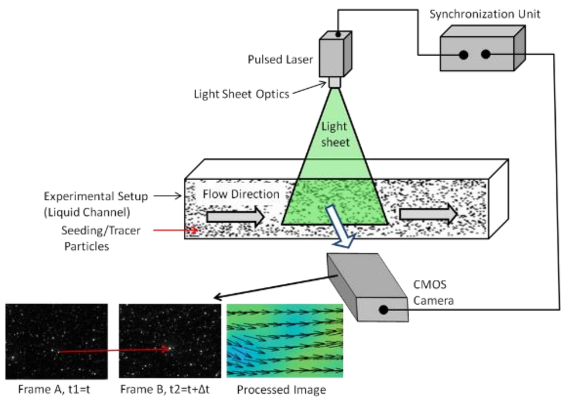
Spatial derivative: space resolution is required

Temporal derivative: time resolution is required

MOTIVATION

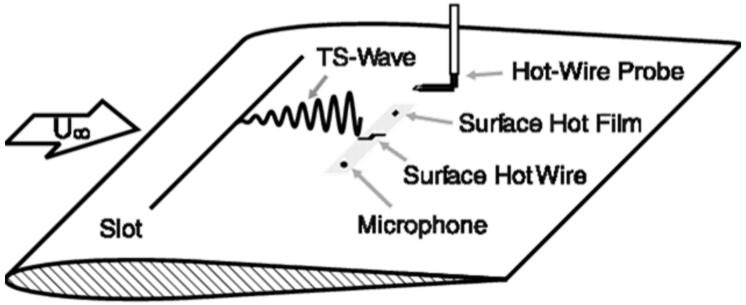
- high cost of time-resolved PIV
- limitation on the frequency of high-speed LASER and cameras

PIV



limited sampling rate
high-sensitive cameras + Nd:YAG LASER:
up to 15 Hz ~ 0.1 m/s
high frequency cameras + Nd:YLF LASER:
up to 10k Hz ~ 10 m/s

probes



advantages:
frequency up to 10 MHz → time derivative
drawbacks:
not easy to interpret
no spatial resolution

MOTIVATION

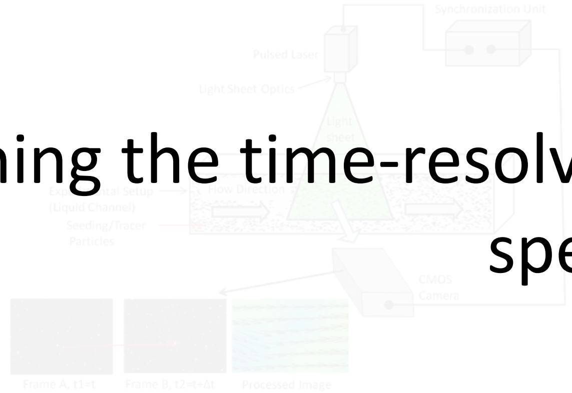
- high cost of time-resolved PIV
- limitation on the frequency of high-speed LASER and cameras

OBJECTIVE

Obtaining the time-resolved velocity field from the combination of low-speed PIV and fast probes.

Then integrating the pressure field.

PIV



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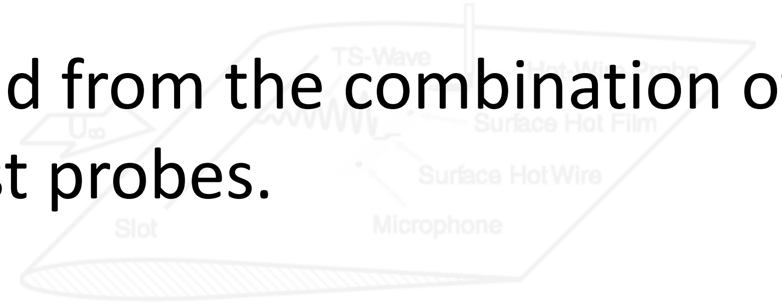
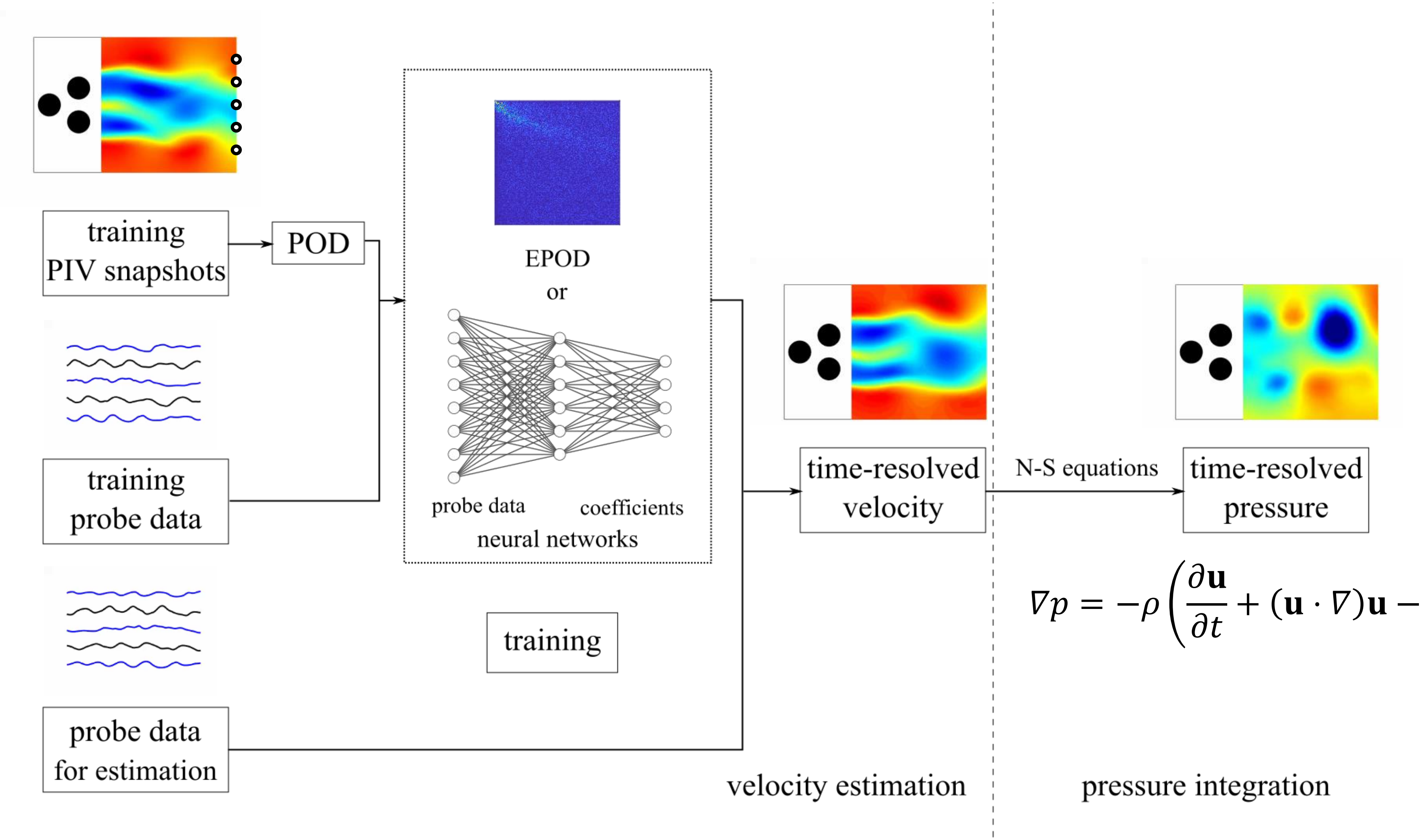


frequency up to 10 MHz → time derivative
drawbacks:
not easy to interpret
no spatial resolution

DATA-DRIVEN DYNAMIC ESTIMATION



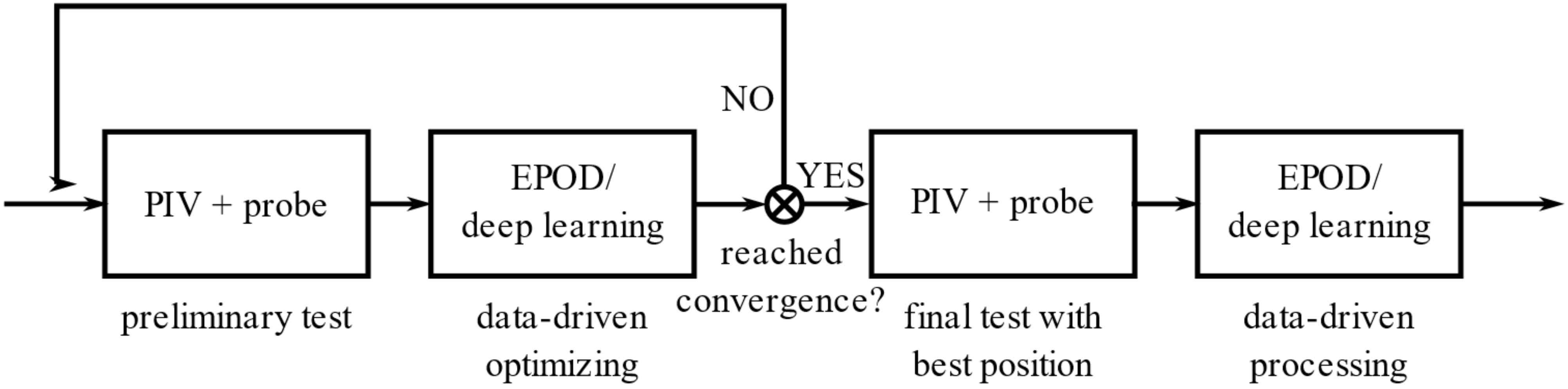
$$\nabla p = -\rho \left(\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\mathbf{u} - \nu \Delta \mathbf{u} \right)$$

Chen et al. (2022) Exp. Therm. Fluid Sci.

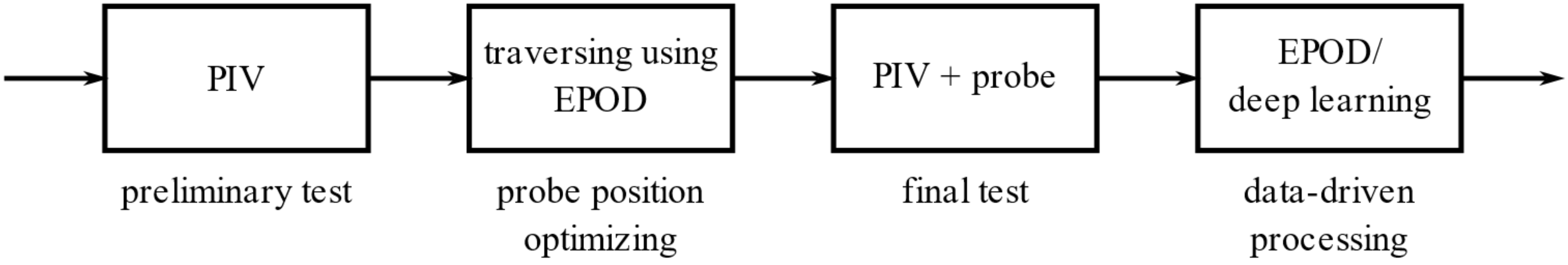
Work 1: Offline optimal sensor positioning

OFFLINE OPTIONAL SENSOR POSITIONING

ONLINE OPTIMIZATION



OFFLINE OPTIMIZATION



OFFLINE OPTIONAL SENSOR POSITIONING

- The offline optimization is sufficient for sensor positioning.
- The accuracy is improved when considering upstream-downstream correlation.
- The positioning from planar PIV field are often acceptable for volumetric measurements.

- Paper published: Chen, Junwei, Marco Raiola, and Stefano Discetti. "An efficient offline sensor placement method for flow estimation." Experimental Thermal and Fluid Science 167 (2025): 111448.

- Code: github.com/erc-nextflow/sensor_placement_V1

- Data: https://doi.org/10.5281/zenodo.15114116

Work 2: Machine learning with overabundant unlabelled samples

ML WITH OVERABUNDANT UNLABELLED SAMPLES

high-repetition-rate field measurements (ideal)

low-repetition-rate field measurements (under limited condition)

paired training dataset

high-repetition-rate point measurements

STRATEGY:

- field propagation to generate more labelled samples
- semi-supervised machine learning

nextflow

Deep learning model $\boldsymbol{f}$ is optimised to predict the POD coefficients

$$\boldsymbol{f}^* = \arg\min_{\boldsymbol{f}} \left\| \boldsymbol{\Sigma} \left[\boldsymbol{\Psi}(t_j) - \boldsymbol{f}\left(\boldsymbol{p}(t_j)\right) \right]^{\mathrm{T}} \right\|_2, \qquad \forall t_j, if\ \boldsymbol{\Psi}(t_j)\ is\ known$$

$\boldsymbol{\Sigma}$, $\boldsymbol{\Psi}$ from POD, t_j time instant, $\boldsymbol{p}$ probe signal

There exists a unique combination of the temporal derivative of POD coefficients $\boldsymbol{\Psi}_{\mathrm{t}}$, when the velocity field is temporal derivable.

Introducing another deep learning model $\boldsymbol{g}$ to predict $\boldsymbol{\Psi}_{\mathrm{t}}$

$$\boldsymbol{g}^* = \arg\min_{\boldsymbol{g}} \left\| \boldsymbol{\Sigma} \left[\frac{\boldsymbol{f}\left(\boldsymbol{p}(t_{j+k})\right) - \boldsymbol{f}\left(\boldsymbol{p}(t_{j-k})\right)}{t_{j+k} - t_{j-k}} - \boldsymbol{g}(\boldsymbol{p}(t_j)) \right]^{\mathrm{T}} \right\|_2,$$

$$\forall t_j, \boldsymbol{\Psi}(t_j)\ is\ known\ or\ unknown$$

ML WITH OVERABUNDANT UNLABELLED SAMPLES

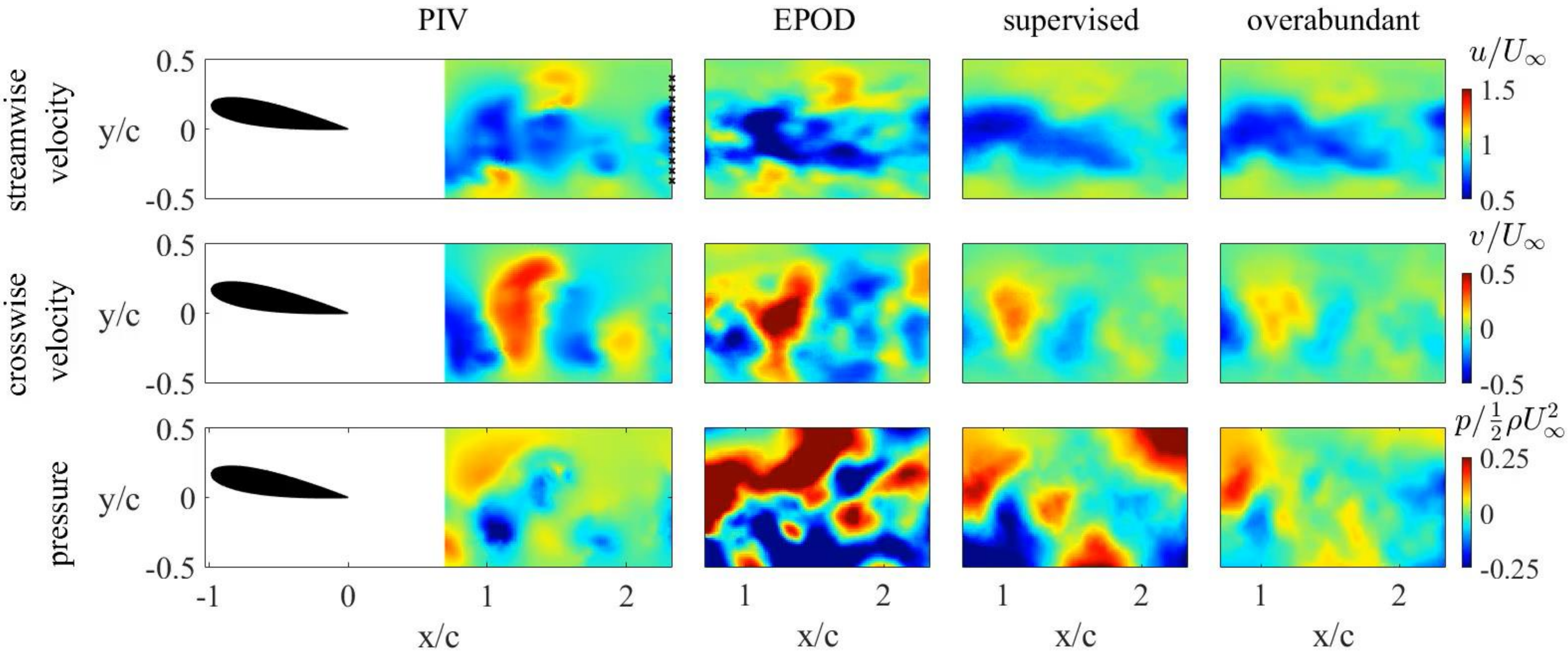
high-repetition-rate field measurements (ideal)

expanded training set

applying semi-supervised machine learning

high-repetition-rate point measurements

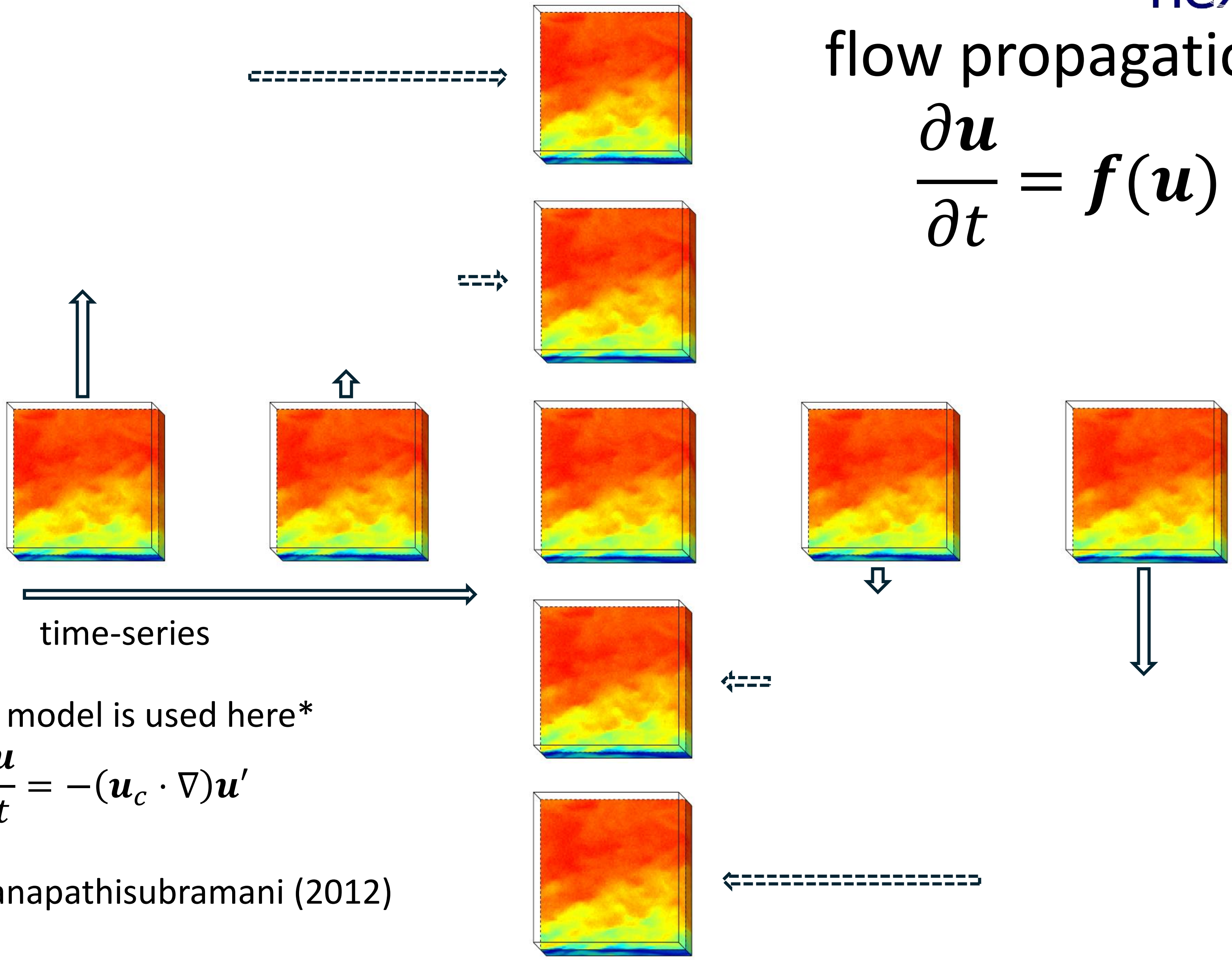
ML WITH OVERABUNDANT UNLABELLED SAMPLES



Side work: Advection-based multiframe iterative correction (AMIC)

flow propagation

$$\frac{\partial \boldsymbol{u}}{\partial t} = \boldsymbol{f}(\boldsymbol{u})$$



An advection model is used here*

$$\frac{\partial \boldsymbol{u}}{\partial t} = -(\boldsymbol{u}_c \cdot \nabla)\boldsymbol{u}'$$

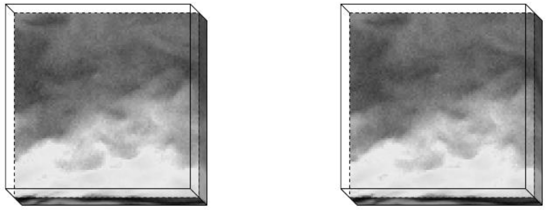
* de Kat & Ganapathisubramani (2012)

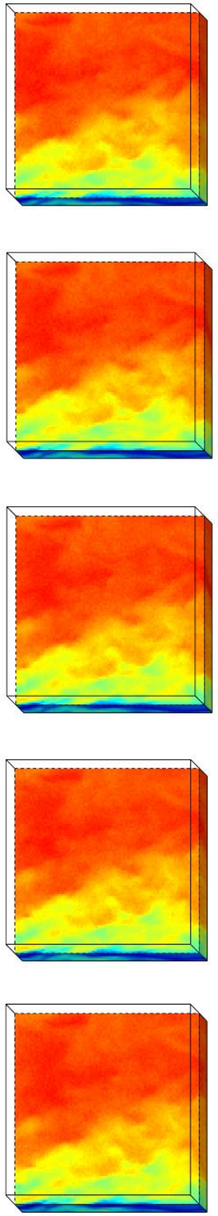
AMIC

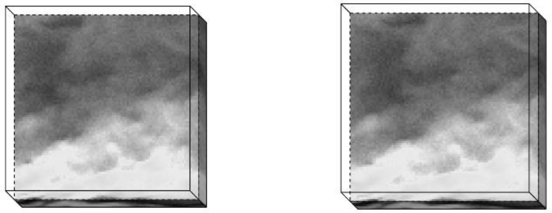
The filter will be applied through the corresponding position of original and propagated frames. reducing the detail loss

flow evolution

$$\frac{\partial \boldsymbol{u}}{\partial t} = \boldsymbol{f}(\boldsymbol{u})$$

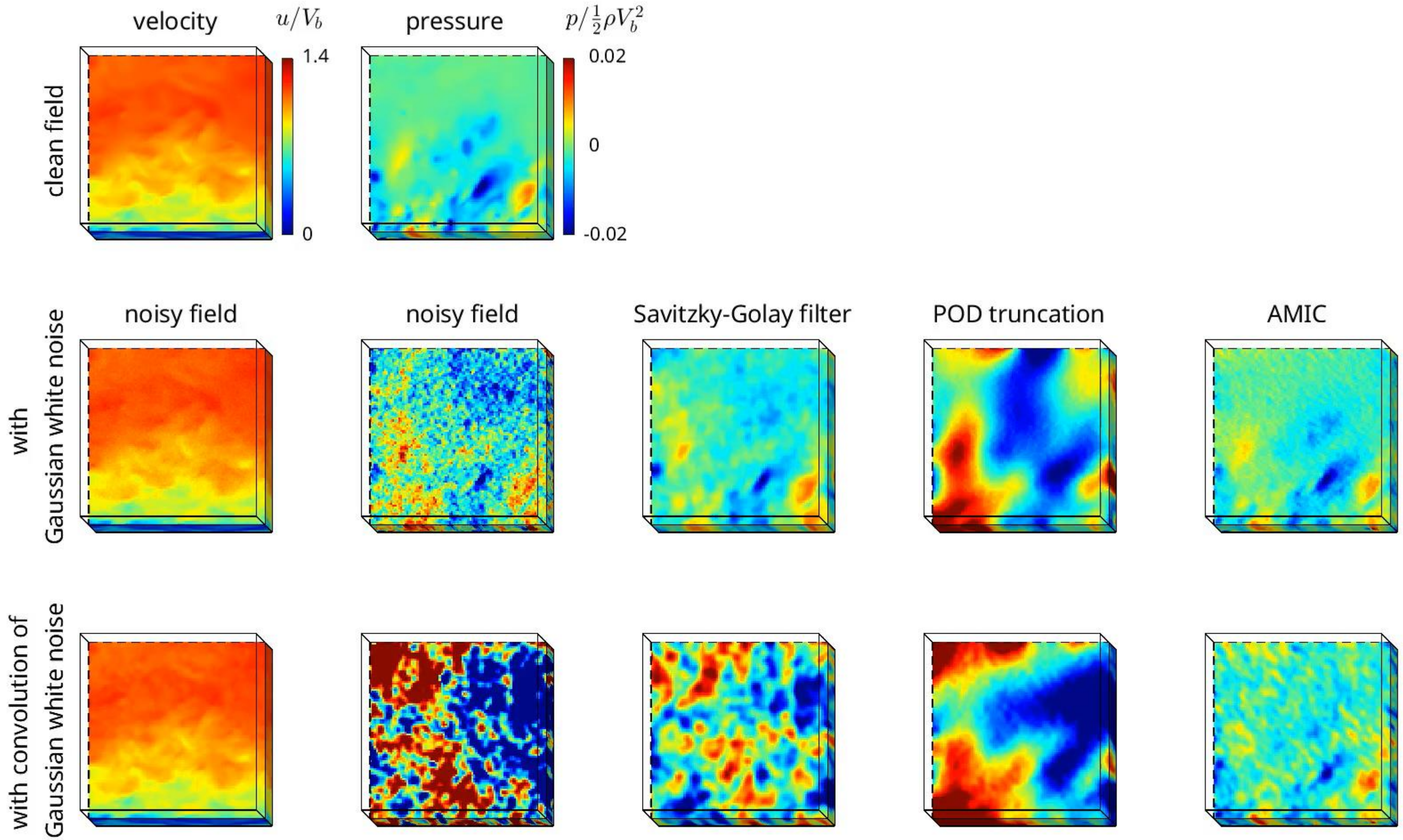




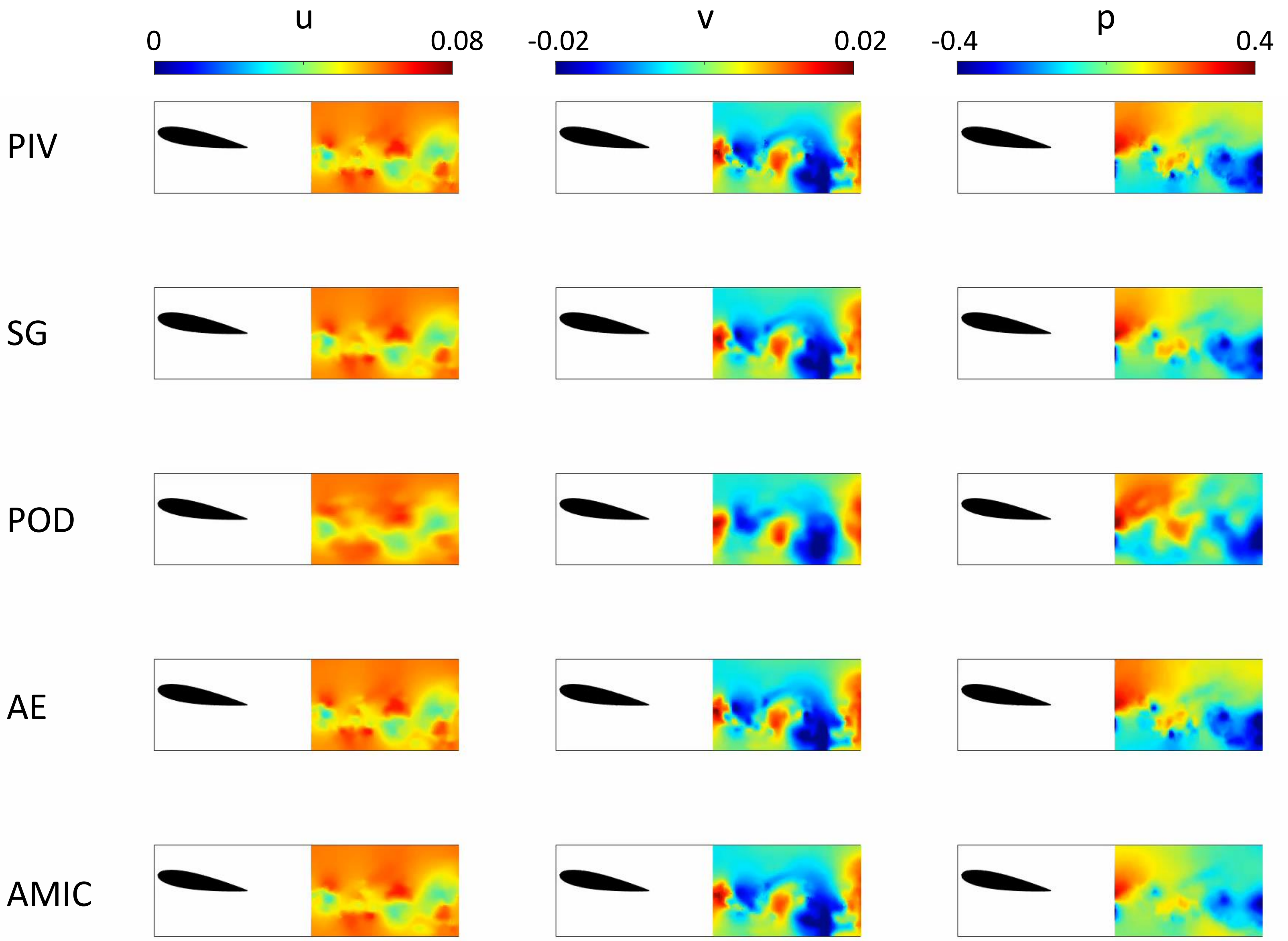


iterative: this procedure will be repeated for several times.

Advection-based multiframe iterative correction (AMIC)


velocity
u/V_b
pressure
$p/\frac{1}{2}\rho V_b^2$
clean field
1.4
0
0.02
0
-0.02
noisy field
noisy field
Savitzky-Golay filter
POD truncation
AMIC
with
Gaussian white noise
with convolution of
Gaussian white noise

AMIC

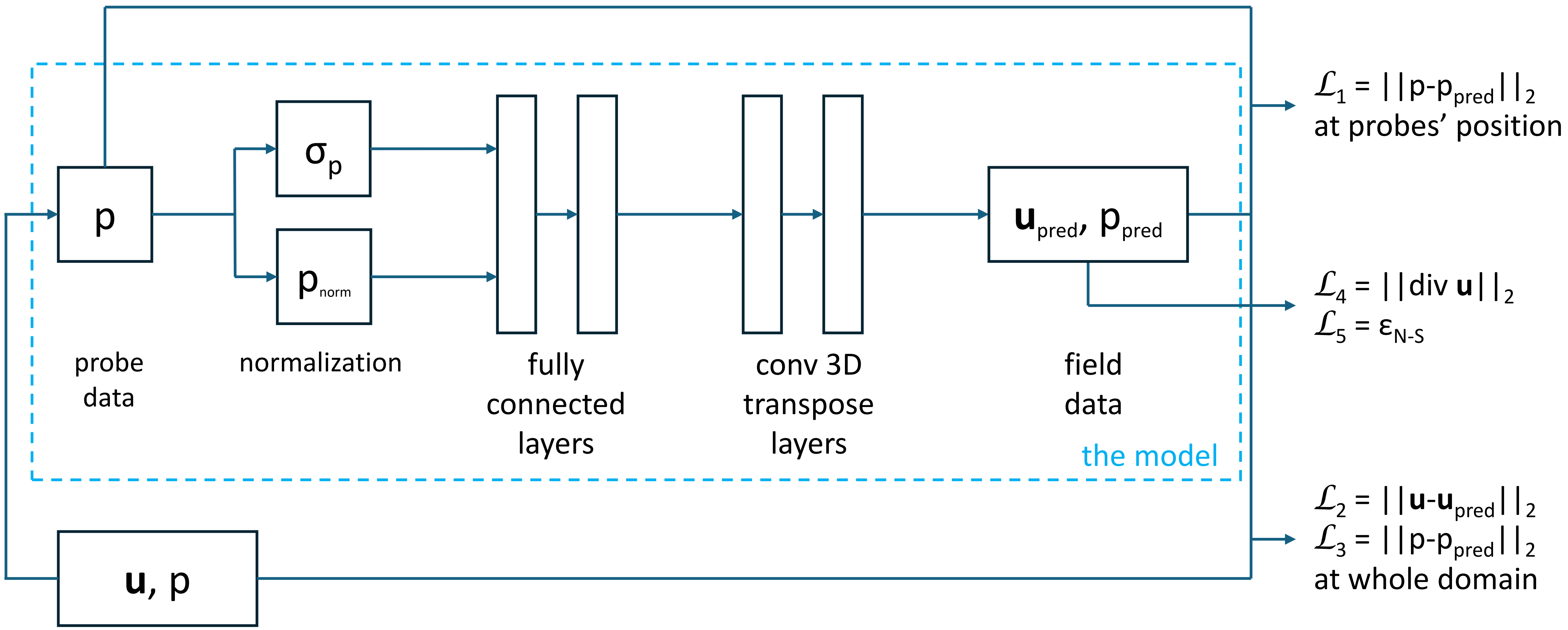


- Paper published: Chen, Junwei, Marco Raiola, and Stefano Discetti. "Advection-based multiframe iterative correction for pressure estimation from velocity fields." Experimental Thermal and Fluid Science 164 (2025): 111407.

- Code: github.com/erc-nextflow/AMIC

- Data: https://doi.org/10.5281/zenodo.14752830

research stay
and
submitting thesis


p
σ_p
p_{norm}
$\mathbf{u}_{pred}$, p_{pred}
probe data
normalization
fully connected layers
conv 3D transpose layers
field data
the model
u, p
$\mathcal{L}_1 = ||p - p_{pred}||_2$
at probes' position
$\mathcal{L}_4 = ||\text{div } \mathbf{u}||_2$
$\mathcal{L}_5 = \varepsilon_{N\text{-}S}$
$\mathcal{L}_2 = ||\mathbf{u} - \mathbf{u}_{pred}||_2$
$\mathcal{L}_3 = ||p - p_{pred}||_2$
at whole domain

Paper published:

- Chen, Junwei, Marco Raiola, and Stefano Discetti. "Advection-based multiframe iterative correction for pressure estimation from velocity fields." Experimental Thermal and Fluid Science 164 (2025): 111407.
- Chen, Junwei, Marco Raiola, and Stefano Discetti. "An efficient offline sensor placement method for flow estimation." Experimental Thermal and Fluid Science 167 (2025): 111448.

conferences:

- 21st International Symposium on Applications of Laser and Imaging Techniques to Fluid Mechanics, Lisbon, Portugal, 08 - 11 July, 2024
- 21st International Symposium on Flow Visualization, Tokyo, Japan, 21-25 June, 2025
- 21st International Symposium on Particle Image Velocimetry, Tokyo, Japan, 26-28 June, 2025

謝謝觀看!

Thanks for your attention!

Gracias!

This project has received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme (grant agreement No. 949085)

European Research Council
Established by the European Commission