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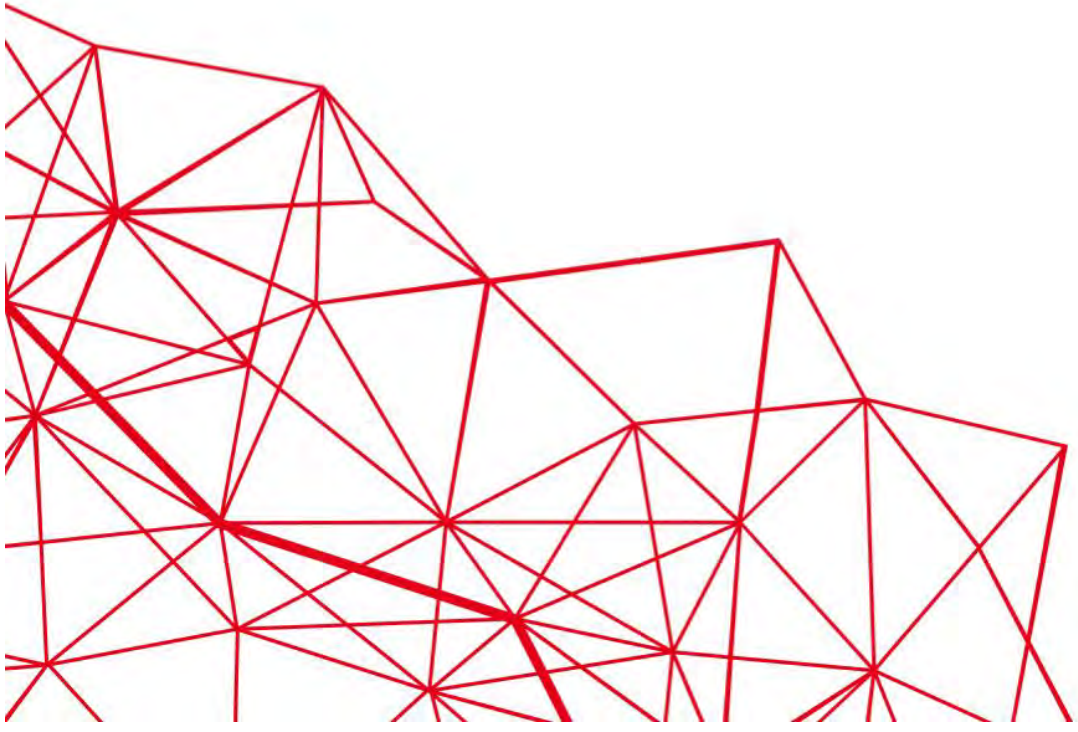

Unsupervised Learning of Particle Image Velocimetry

ISC 2020 Digital

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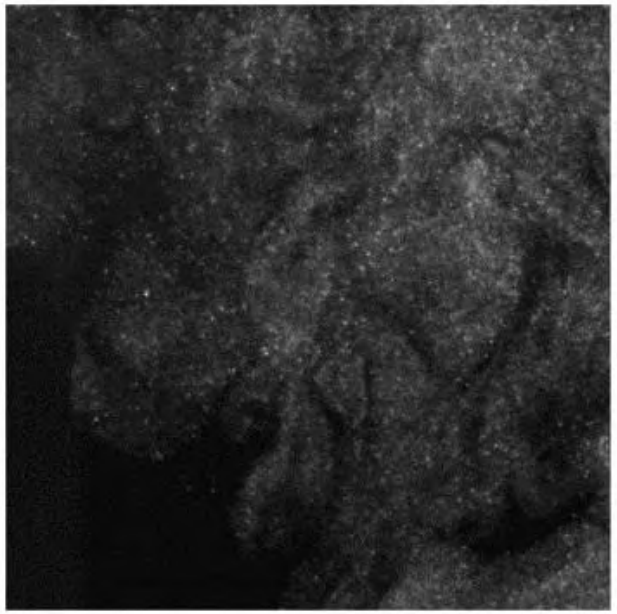
Outline

- Particle Image Velocimetry (PIV)
  - From traditional method to deep learning method
- Unsupervised learning of PIV
  - Our unsupervised learning method of PIV
- Results
  - Comparisons with traditional PIV and supervised learning method
  - Test on real experimental data
- More results

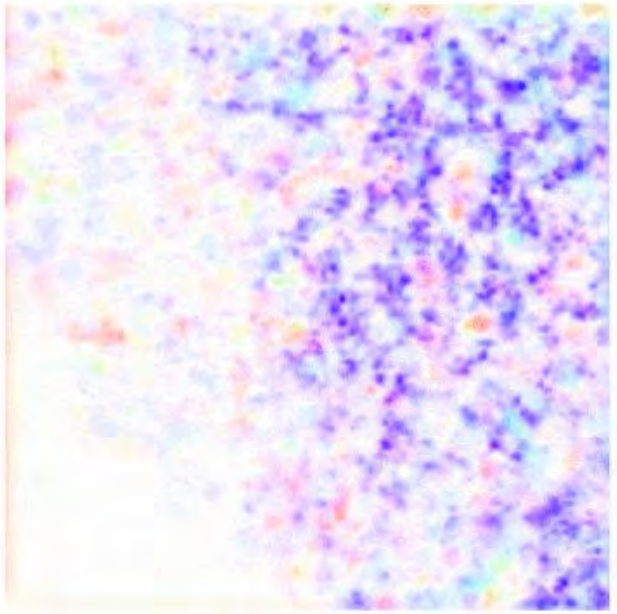
Particle Image Velocimetry

Introduction

Particle Image Velocimetry (PIV) is one of the most popular measurement techniques in experimental fluid dynamics.



Particle images



Velocity field

Traditional Methods

- **Cross-correlation method**

  Calculates a displacement by searching for the maximum cross-correlation between two interrogation windows from an image pair.

Relatively Efficient	Spatially sparse
Easy to implement	Requires post-processing

Traditional Methods

- **Optical flow method**

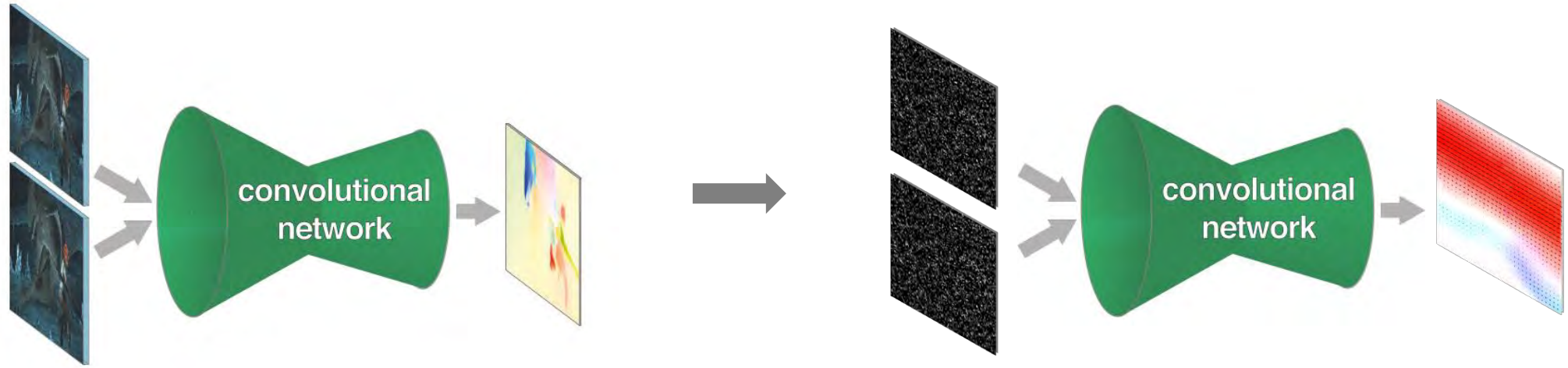
  Treats the PIV problem through the solution of an **optimisation problem**, seeking the minimisation of an objective function.

Dense output

Time consuming

Deep learning methods

- **From optical flow to fluid flow**



FlowNet

Left image Source: A. Dosovitskiy, P. Fischer, E. Ilg, P. Hausser, C. Hazirbas, V. Golkov, P. Van der Smagt, D. Cremers, and T. Brox.: Flownet: Learning optical flow with convolutional networks. In Proceedings of the IEEE International Conference on Computer Vision, pp. 2758|2766 (2015)

Deep learning methods

- **Supervised learning – PIV**

Basic idea: Train network using data with known velocity field

(Typically synthetic data e.g. simulation results)

Several network architectures have been researched:

PIV-DCNN, PIV-FlowNet, PIV-LiteFlowNet etc.

Y. Lee, H. Yang, and Z. Yin.: PIV-DCNN: cascaded deep convolutional neural networks for particle image velocimetry. Experiments in Fluids, vol. 58, no. 12, article number 171 (2017)

S. Cai, S. Zhou, C. Xu, and Q. Gao.: Dense motion estimation of particle images via a convolutional neural network. Experiments in Fluids, vol. 60, no. 4, article number 73 (2019)

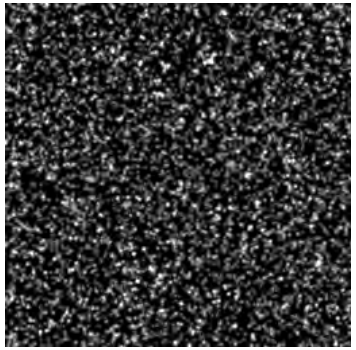
S. Cai, J. Liang, Q. Gao, C. Xu, R. Wei.: Particle image velocimetry based on a deep learning motion estimator. IEEE Transactions on Instrumentation and Measurement (2019b)

Challenges

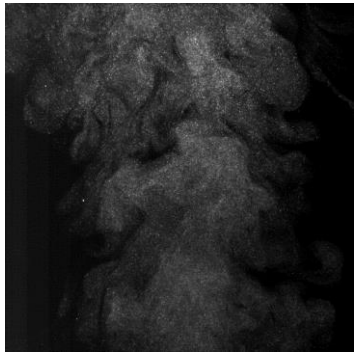
- **Insufficient data**

There is no easily available ground truth data in real world scenarios.

- **Domain mismatch**



Training data



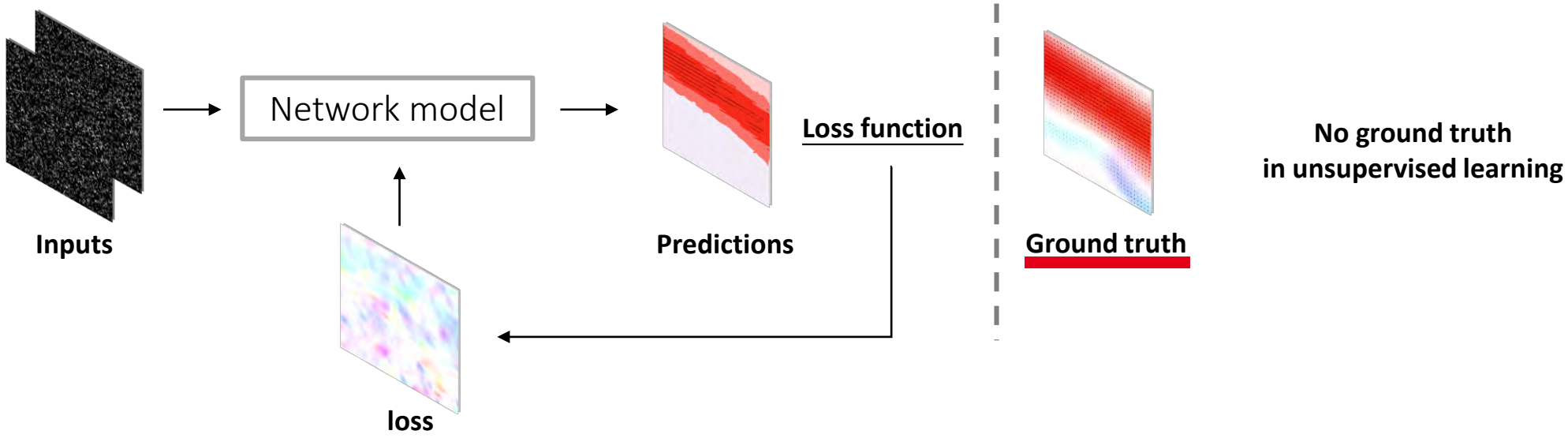
Potential Test data

Can we go further?

Unsupervised learning of PIV

Loss function

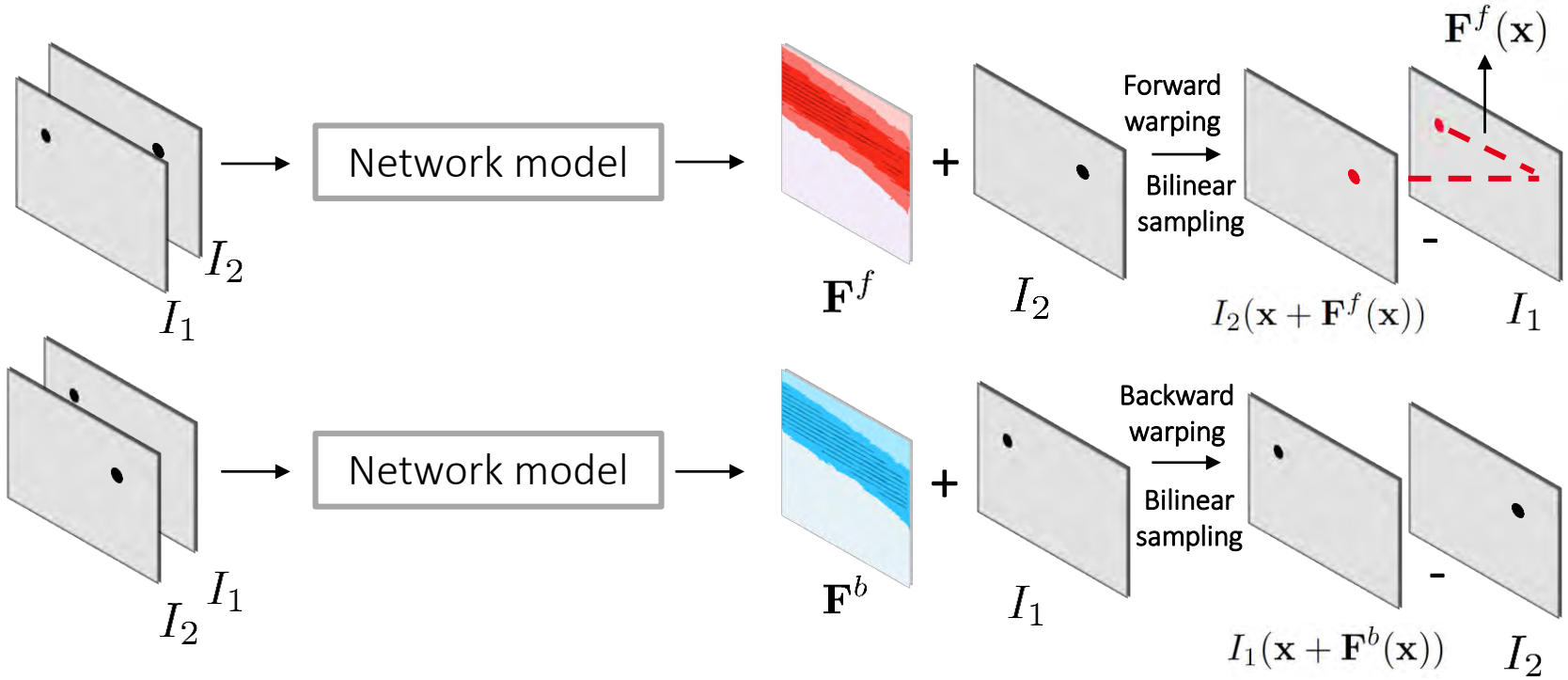
- **Unsupervised learning vs Supervised learning**

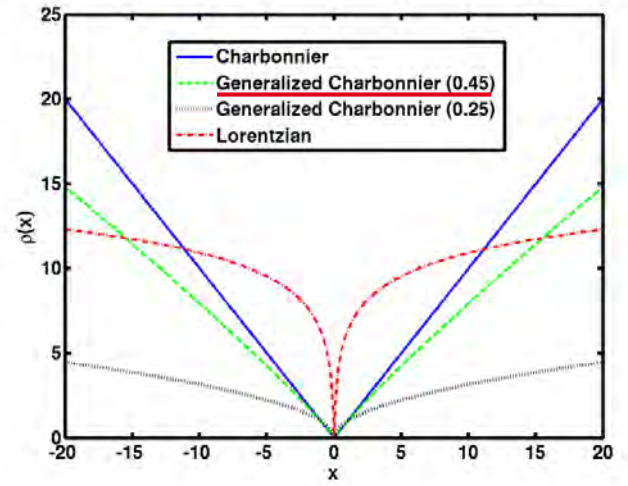


How to design the loss function?

Loss function

- **Photometric loss**





ρ: Generalized Charbonnier penalty function

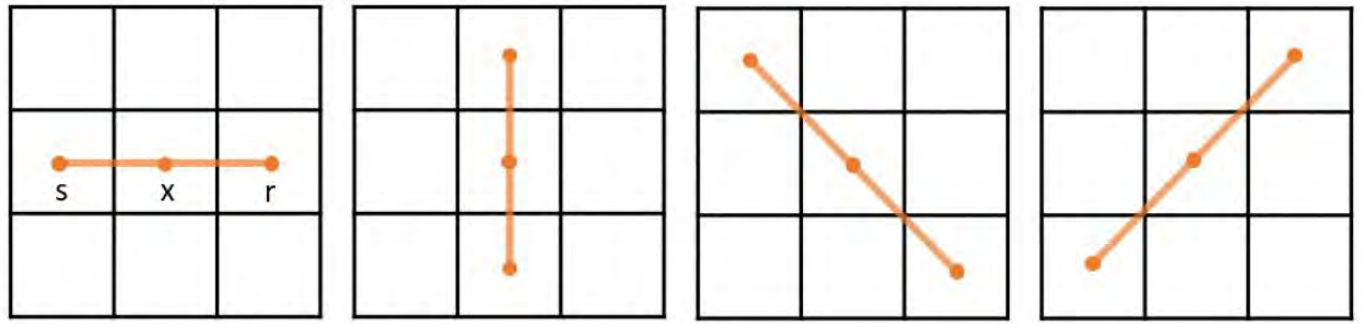
D. Sun, et al. IJCV (2014)

Photometric loss

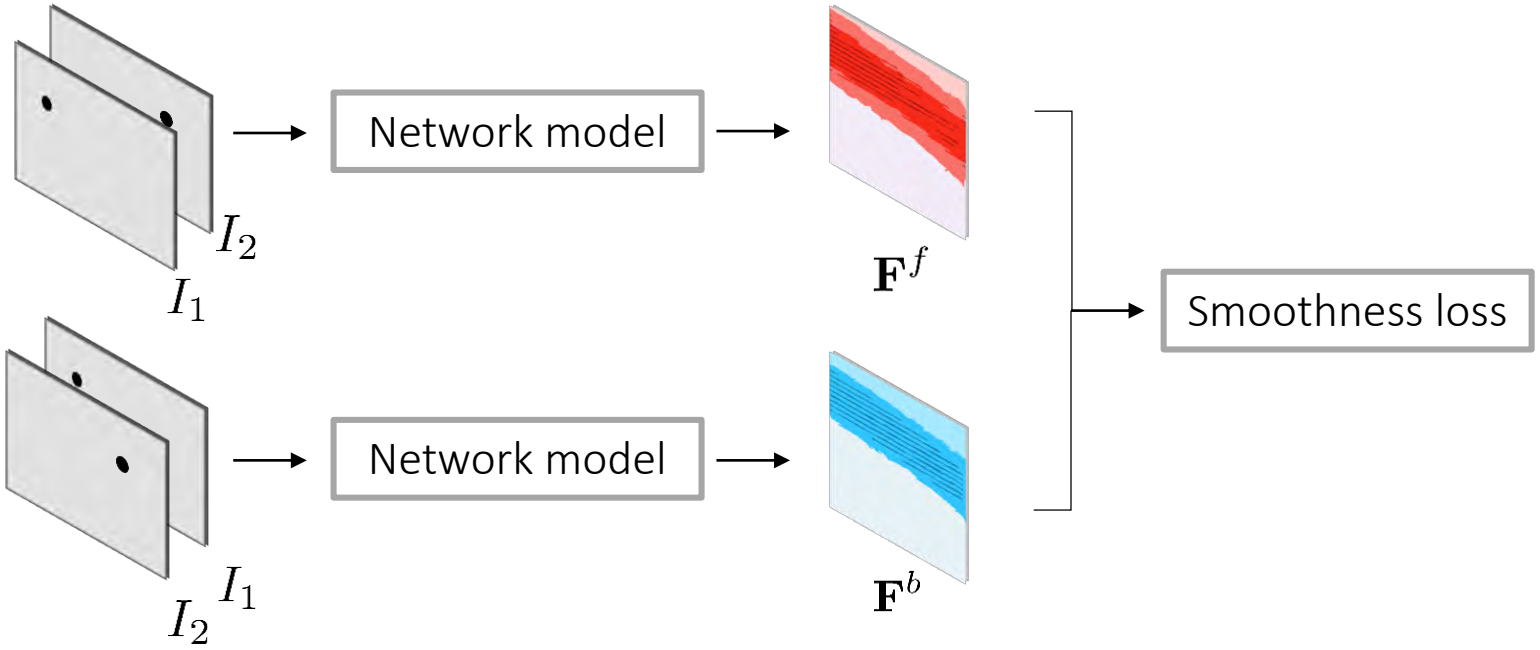
$$L_P(I_1, I_2, \mathbf{F}^f, \mathbf{F}^b) = \sum_{\mathbf{x}\in P} \rho\left(I_1(\mathbf{x}) - I_2(\mathbf{x}+\mathbf{F}^f(\mathbf{x}))\right) + \rho\left(I_2(\mathbf{x}) - I_1(\mathbf{x}+\mathbf{F}^b(\mathbf{x}))\right)$$

Bilinear sampling: M. Jaderberg, et.al.: Spatial transformer networks. In NIPS'15

Loss function



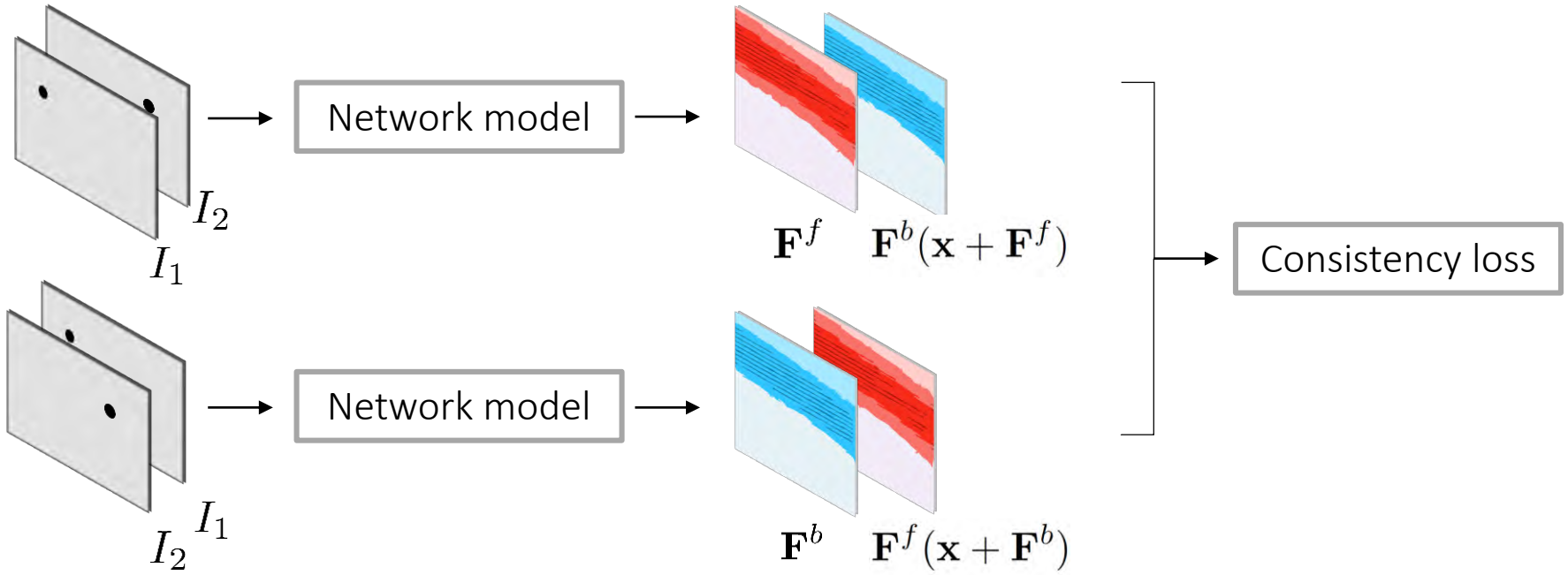
- **Smoothness loss**



$$L_S(\mathbf{F}^f, \mathbf{F}^b) = \sum_{(\mathbf{s},\mathbf{r})\in\mathbf{N}(\mathbf{x})} \sum_{\mathbf{x}\in P} \rho\left(\mathbf{F}^f(\mathbf{s}) - 2\mathbf{F}^f(\mathbf{x}) + \mathbf{F}^f(\mathbf{r})\right) + \rho\left(\mathbf{F}^b(\mathbf{s}) - 2\mathbf{F}^b(\mathbf{x}) + \mathbf{F}^b(\mathbf{r})\right)$$

Loss function

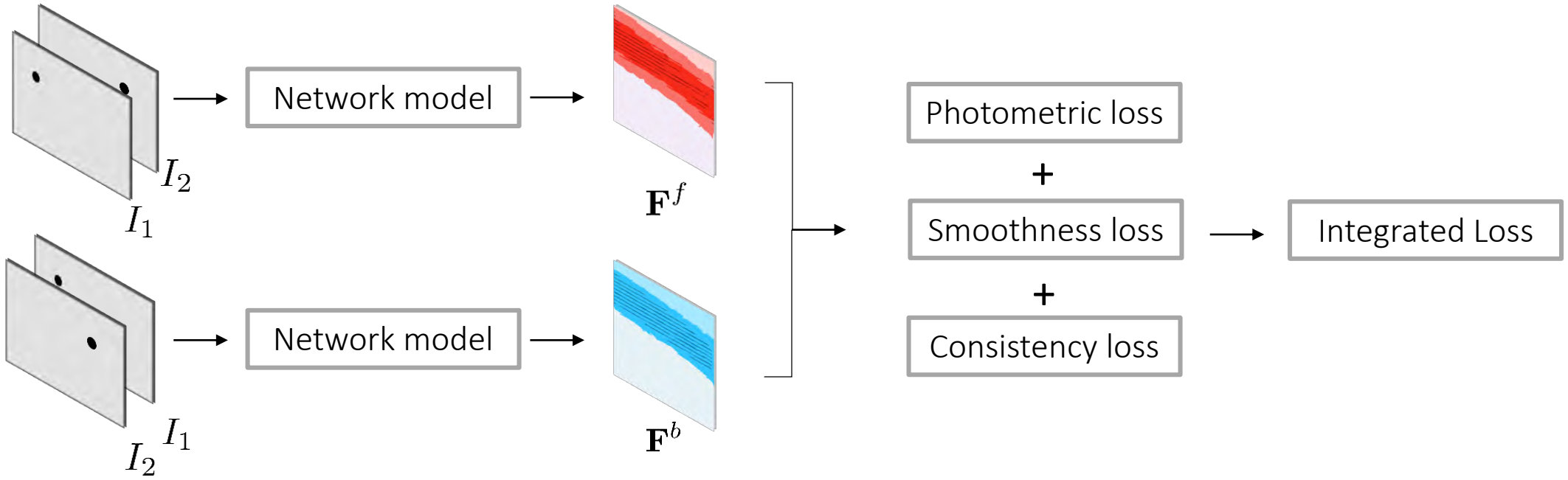
- **Consistency loss**



$$L_C(\mathbf{F}^f, \mathbf{F}^b) = \sum_{\mathbf{x}\in P} \rho\left(\mathbf{F}^f + \mathbf{F}^b(\mathbf{x}+\mathbf{F}^f)\right) + \rho\left(\mathbf{F}^b + \mathbf{F}^f(\mathbf{x}+\mathbf{F}^b)\right)$$

Loss function

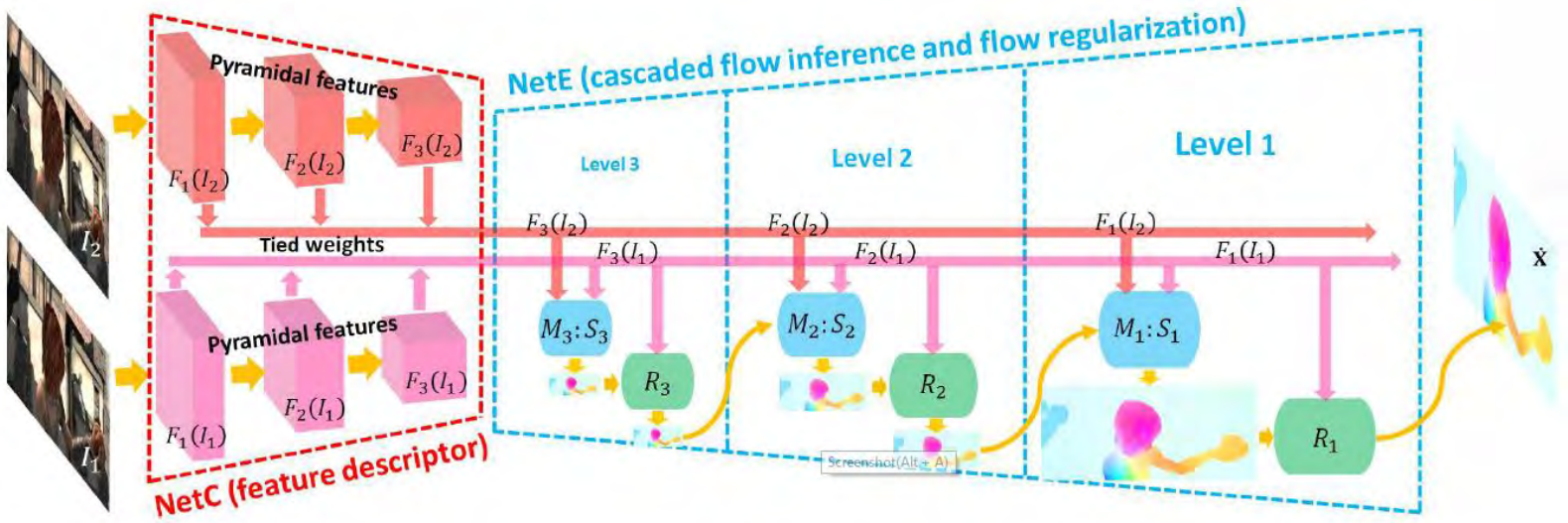
- **Final integrated loss**



$$L(I_1, I_2, \mathbf{F}^f, \mathbf{F}^b) = \lambda_D L_D + \lambda_S L_S + \lambda_C L_C$$

Network Architecture

- **LiteFlowNet architecture**



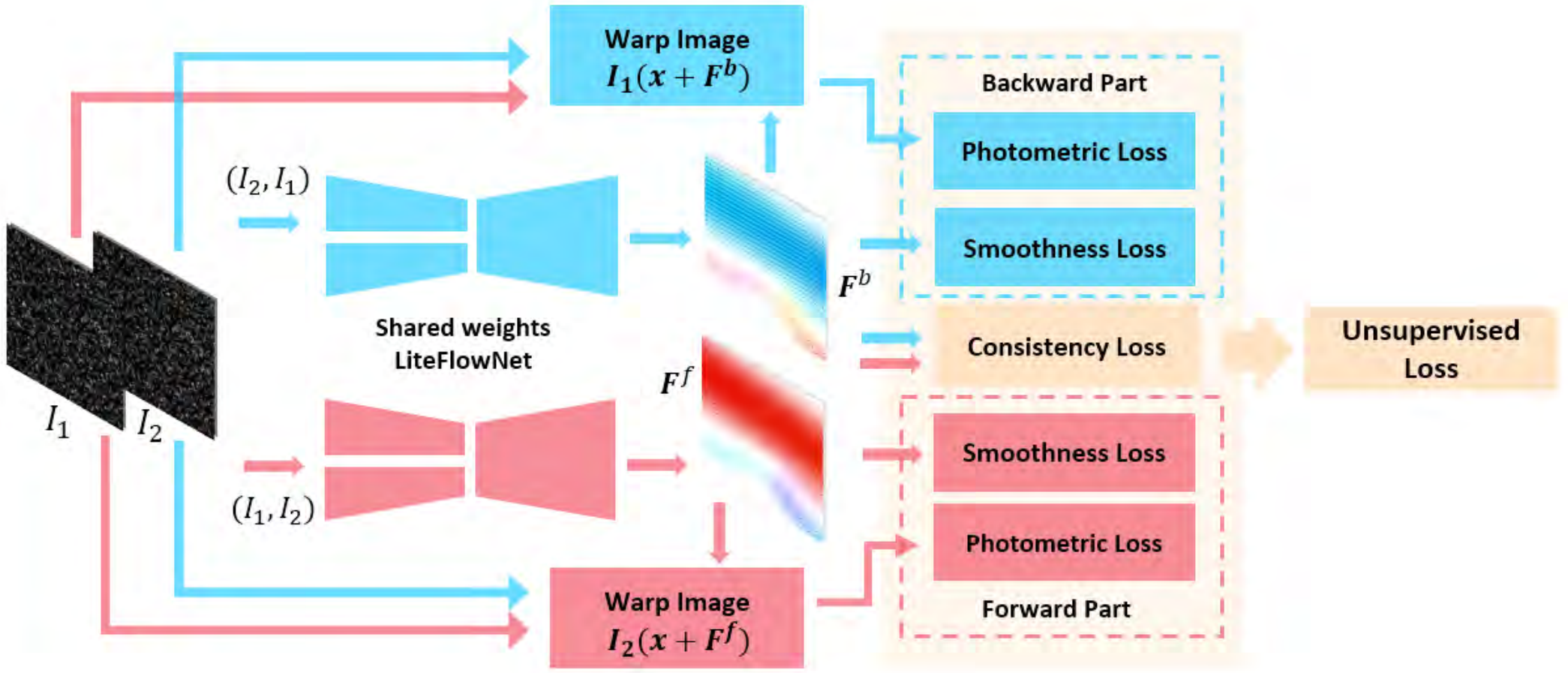
Main Features

1. Compact model size
(compared to FlowNet)

2.Feature warping module
(Address large displacement)

T. Hui, X. Tang, and C. Loy.: LiteFlowNet: A lightweight convolutional neural network for optical flow estimation. In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp. 8981{8989 (2018)

Final Pipeline



UnLiteFlowNet-PIV

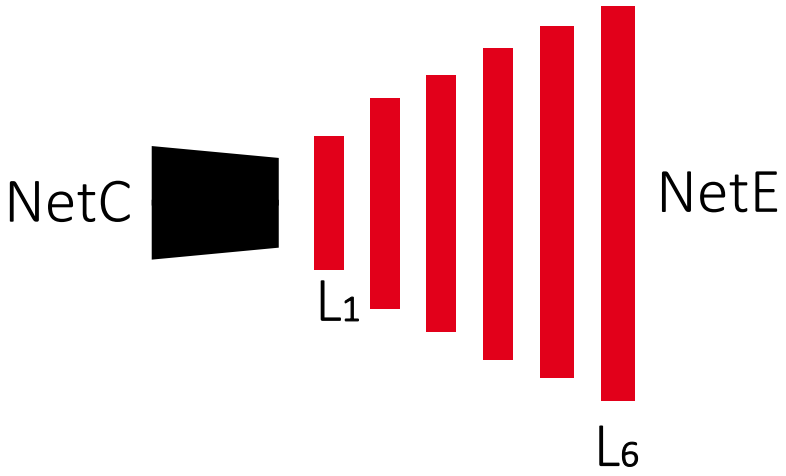
Training details

- **Data:** 15,050 particle image pairs (half was used in training)

  PIV dataset

  Shengze Cai, Shichao Zhou, Chao Xu, Qi Gao. Dense motion estimation of particle images via a convolutional neural network, Exp Fluids, 2019

- **Training iterations**: 40,000 iterations with a batch size of 8
- **Ensemble loss strategy of multi resolution outputs is applied**



$$L_T = \sum_i w_i L_i$$

Results

Metrics

- Average Endpoint Error(AEE)

Averaged Euclidean norm of differences between estimated flow and ground truth flow matrix

$$\mathrm{AEE} = \left\| \mathbf{F}^e - \mathbf{F}^g \right\|_2$$

Comparison

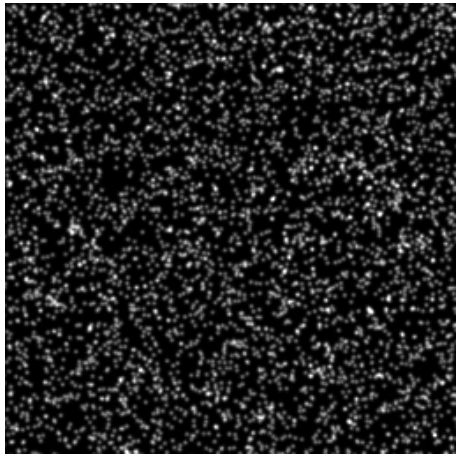
Methods	Back-Step		Cylinder		JHTDB channel		DNS turbulence		SQG	
	train	test	train	test	train	test	train	test	train	test
WIDIM [12]	-	3.4	-	8.3	-	8.4	-	30.4	-	45.7
HS optical flow [12]	-	4.5	-	7.0	-	6.9	-	13.5	-	15.6
PIV-NetS-noRef [11]	13.6	13.9	19.8	19.4	24.6	24.7	50.6	52.5	51.9	52.5
PIV-NetS [11]	5.8	5.9	6.9	7.2	16.3	15.5	27.1	28.2	28.9	29.4
PIV-LiteFlowNet [12]	5.5	5.6	8.7	8.3	10.9	10.4	18.8	19.6	19.8	20.2
PIV-LiteFlowNet-en [12]	3.2	3.3	5.2	4.9	7.9	7.5	11.6	12.2	12.4	12.6
UnLiteFlowNet-PIV	-	10.1	-	7.8	-	9.6	-	13.5	-	19.7

(The error unit is set to pixel per 100 pixels for easier comparison)

S. Cai, S. Zhou, C. Xu, and Q. Gao.: Dense motion estimation of particle images via a convolutional neural network. Experiments in Fluids, vol. 60, no. 4, article number 73 (2019)

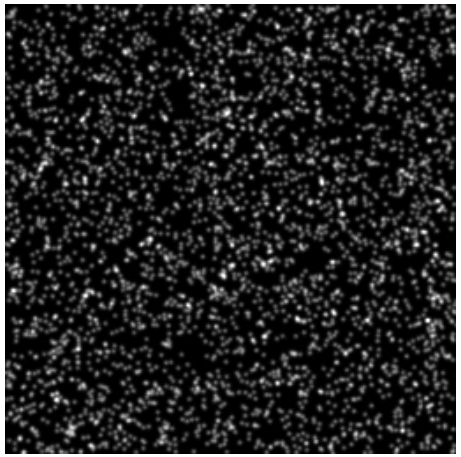
S. Cai, J. Liang, Q. Gao, C. Xu, R. Wei.: Particle image velocimetry based on a deep learning motion estimator. IEEE Transactions on Instrumentation and Measurement (2019b)

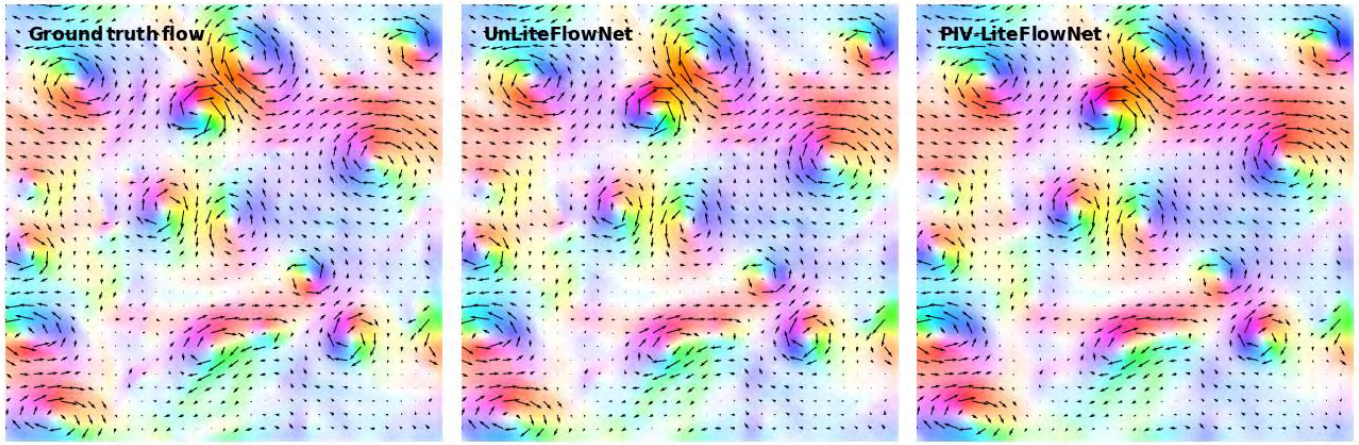
Results



D. Sun, et al. IJCV (2014)

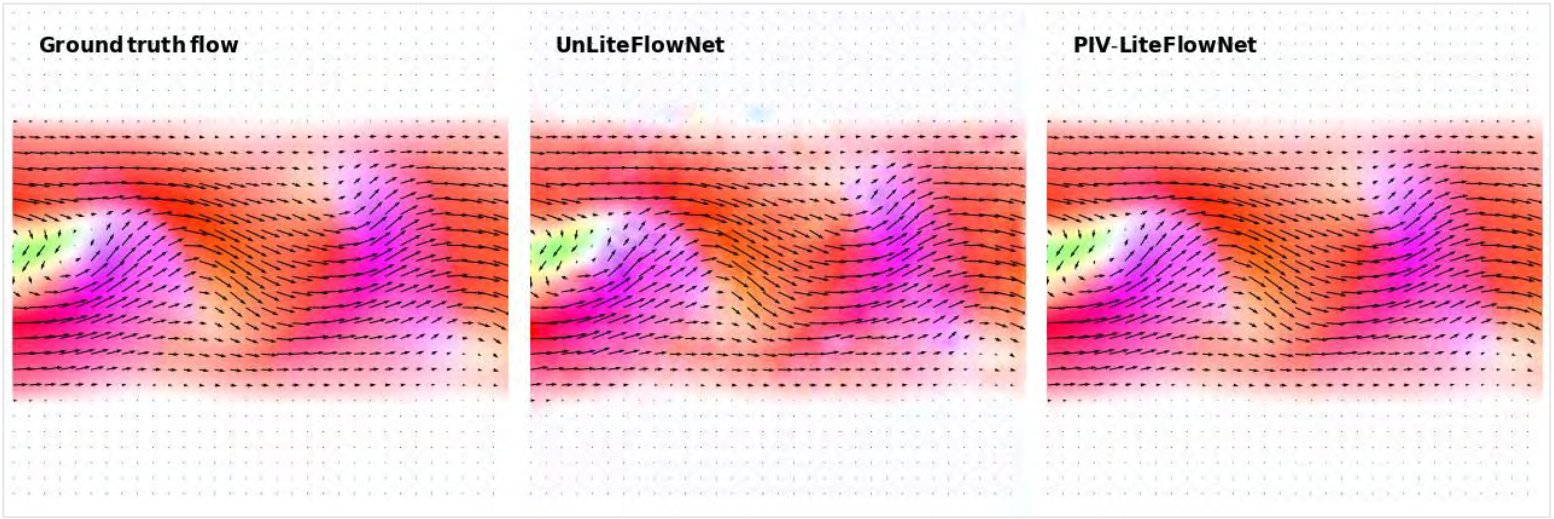
Flow past a backward facing step





Sea Surface Flow (Driven by SQG)

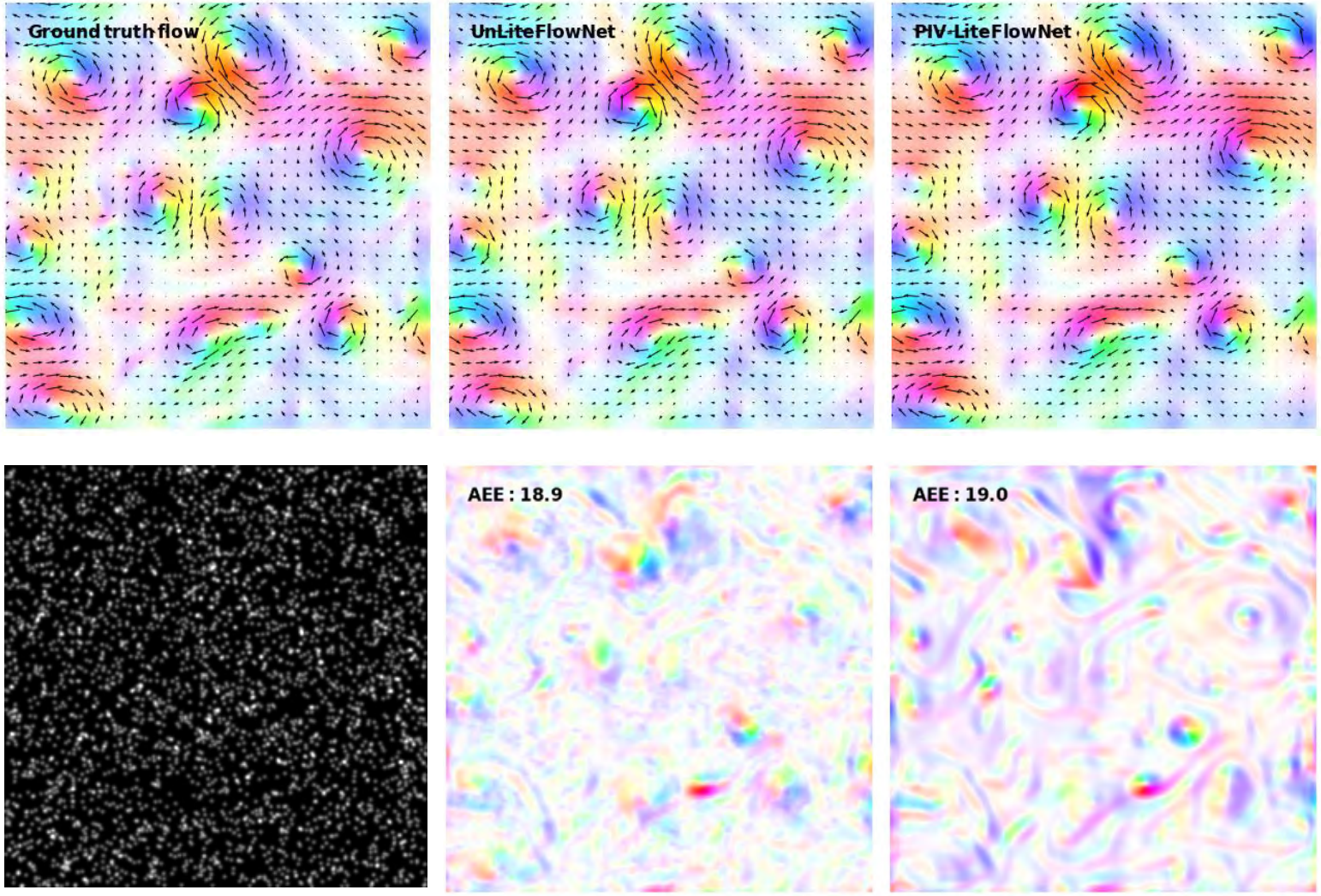
Results



Flow past a circular cylinder

Error (white = zero)

Results



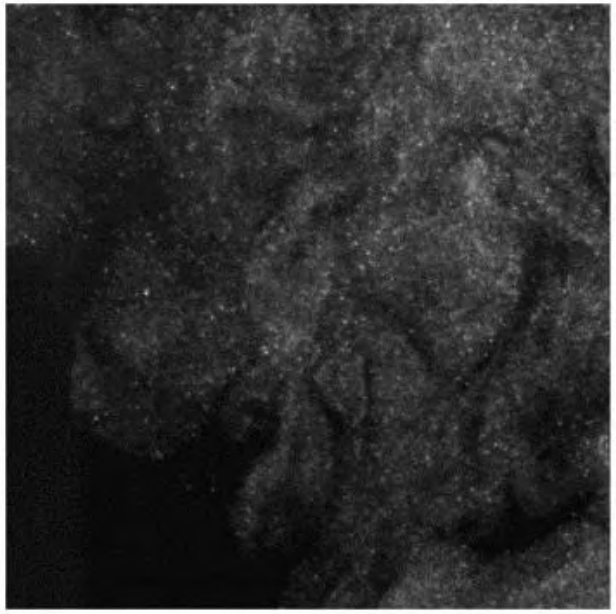
Sea Surface Flow
(Driven by SQG)

Error (white = zero)

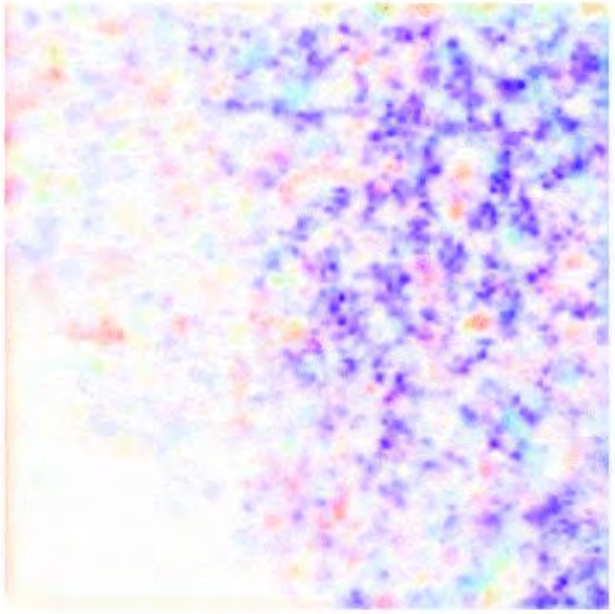
Real Experimental data

Time-resolved Jet Flow

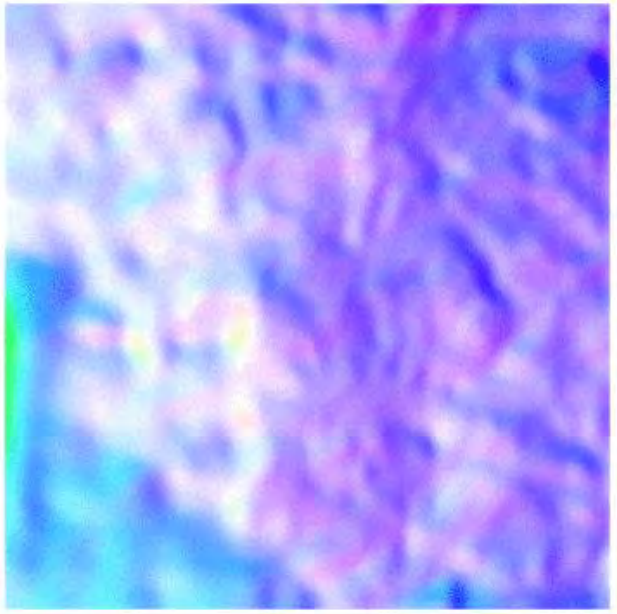
(Experimental data, no ground truth)



Inputs



UnLiteFlowNet-PIV
(Our unsupervised method,
Trained by photometric loss only)



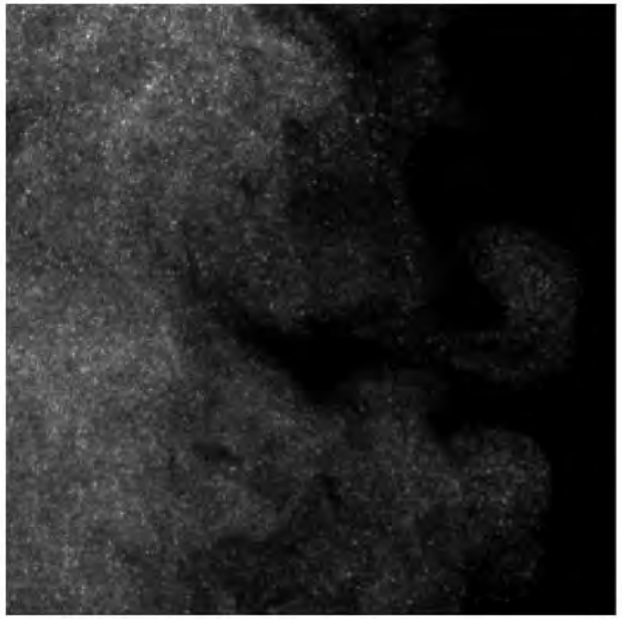
PIV-LiteFlowNet
(Supervised method)

Data source: https://www.pivchallenge.org/pub05/index.html#c

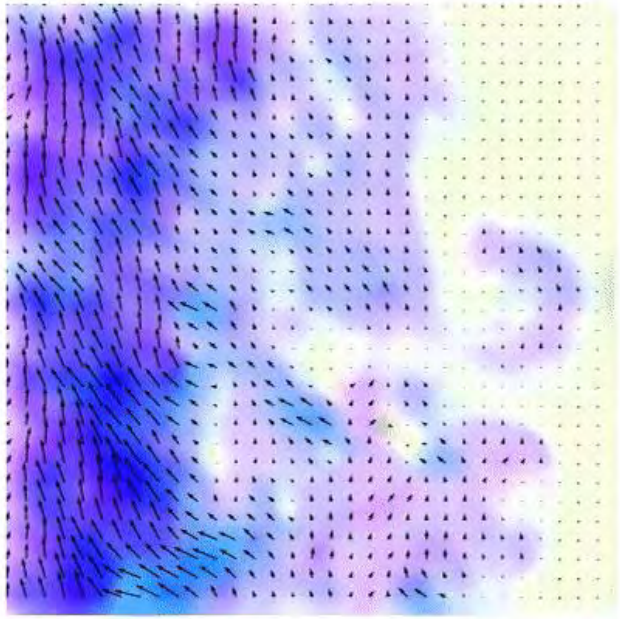
Real Experimental data

Time-resolved Jet Flow

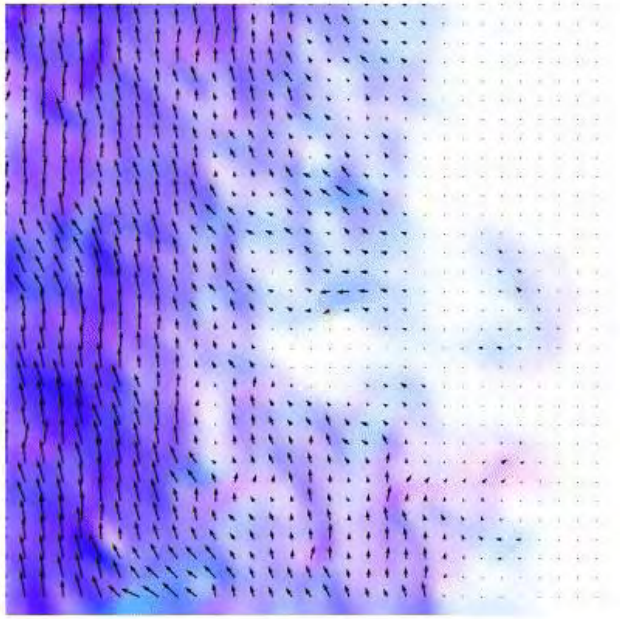
(Experimental data, no ground truth)



Inputs



UnLiteFlowNet-PIV
(Our unsupervised method,
Trained by full integrated loss)



PIV-LiteFlowNet
(Supervised method)

Data source: https://www.pivchallenge.org/pub05/index.html#c

Conclusions

- **Competitive results**

  Competitive results compared with classical PIV methods as well as existing supervised learning based methods

- **Potential generalization ability**

  Potential to generalize to complex real-world flow scenarios where ground truth is effectively unknowable

Project page with open source codes:

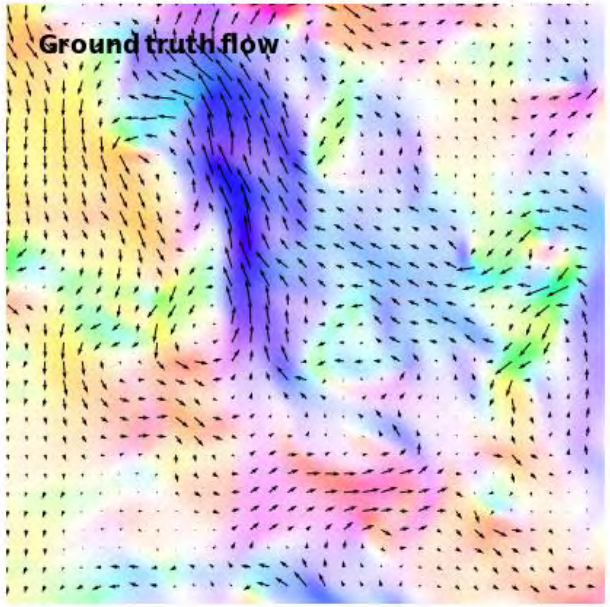
https://github.com/erizmr/UnLiteFlowNet-PIV

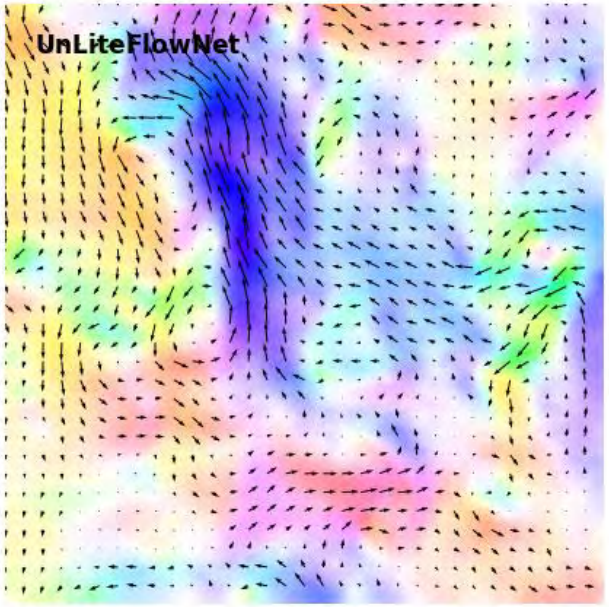
Contact:

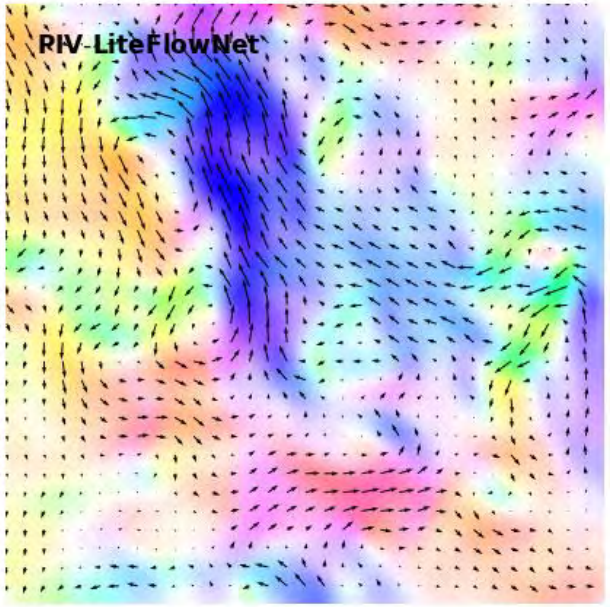
mingrui.zhang18@imperial.ac.uk

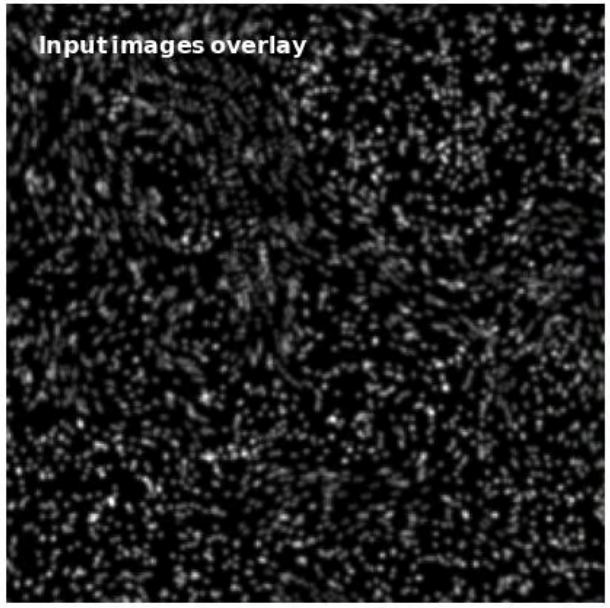
More Results

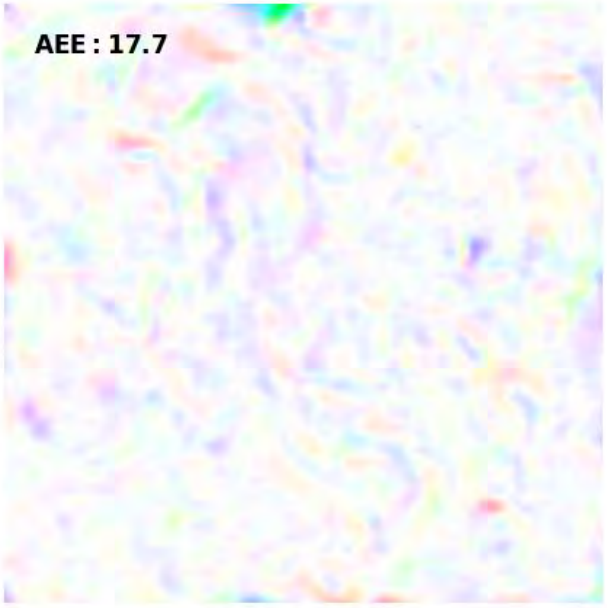
JHTDB
Isotropic turbulence

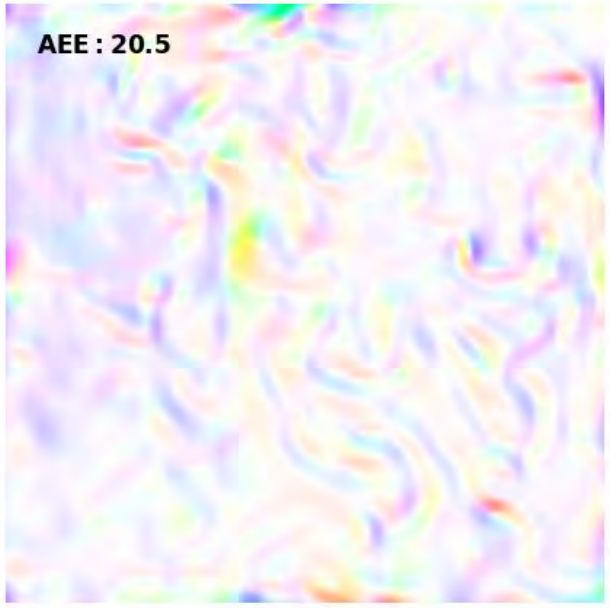




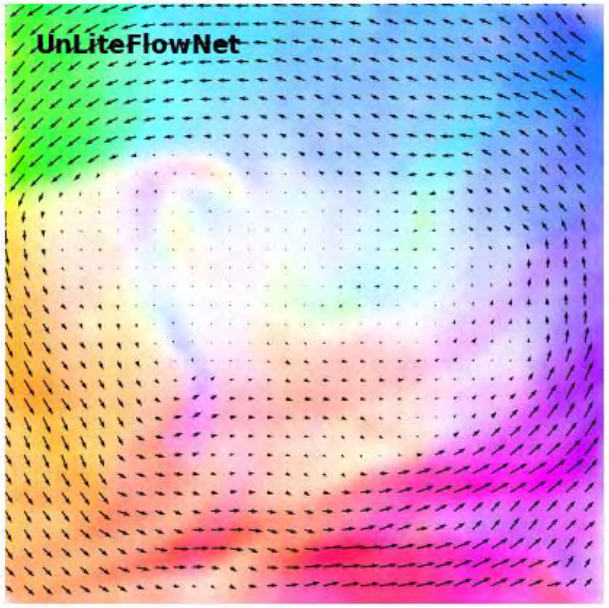


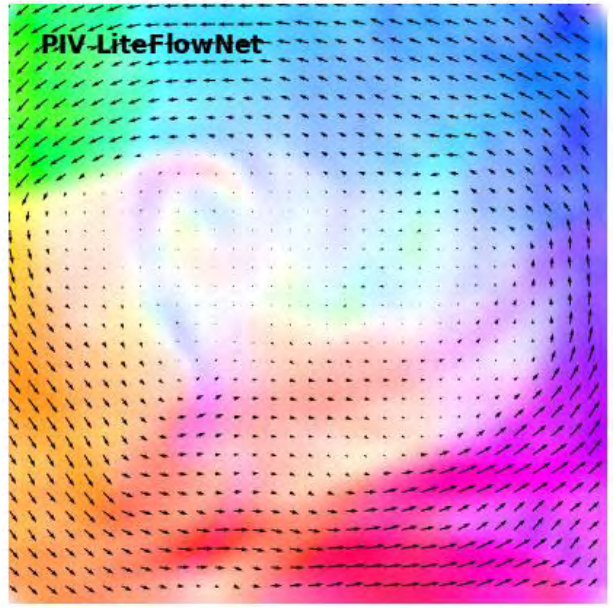


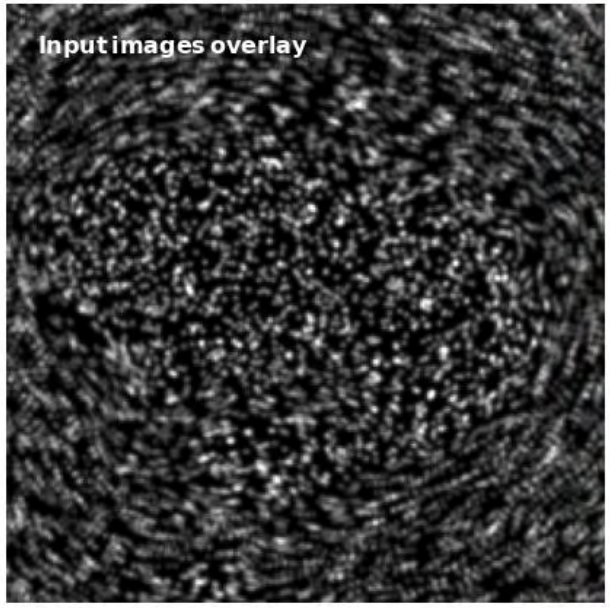


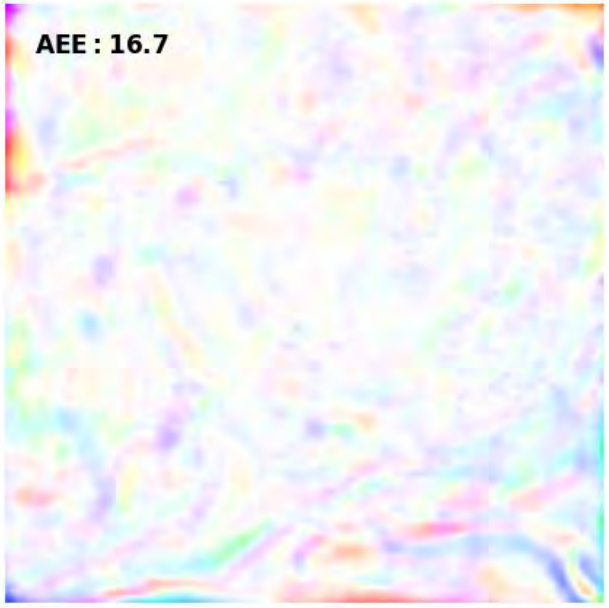


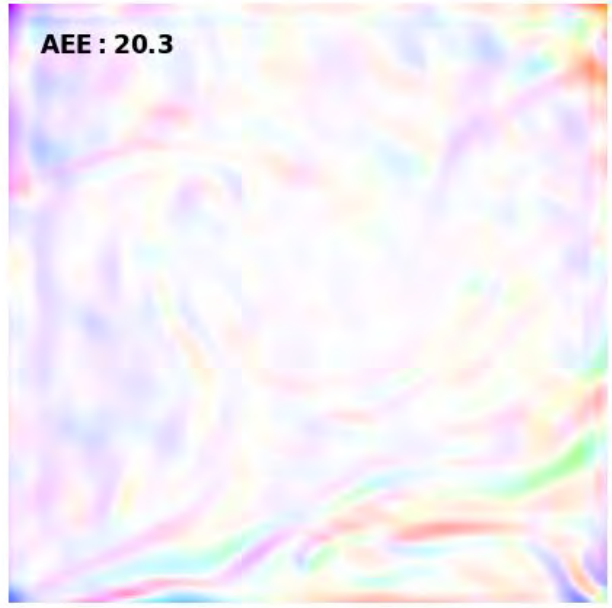
JHTDB
DNS turbulence



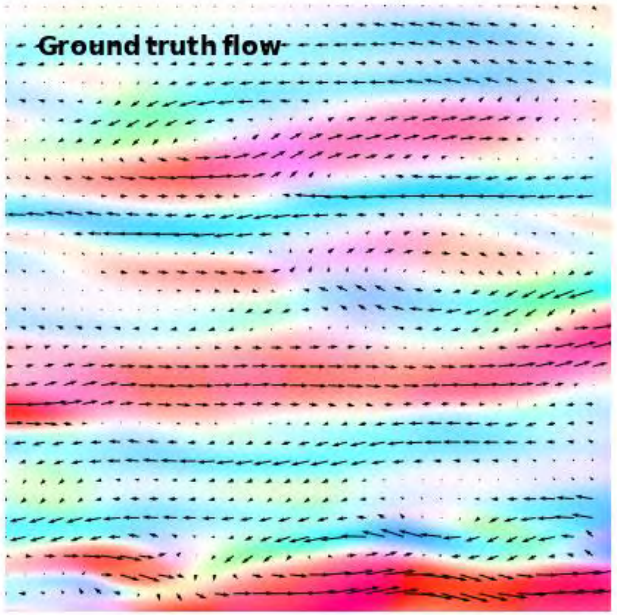


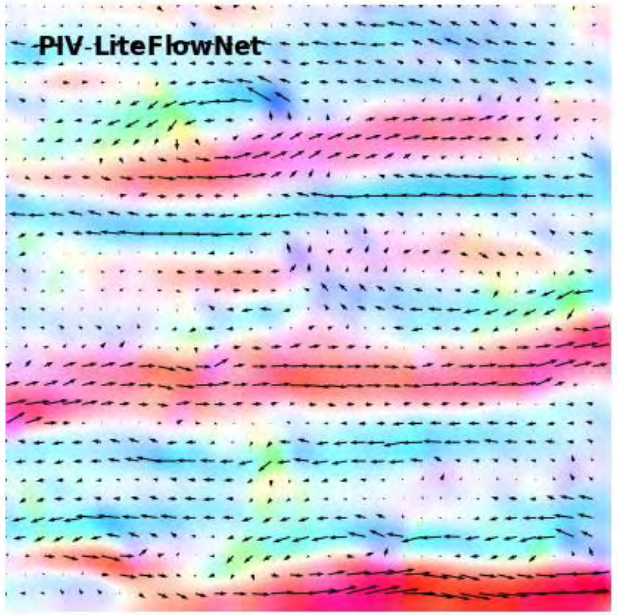


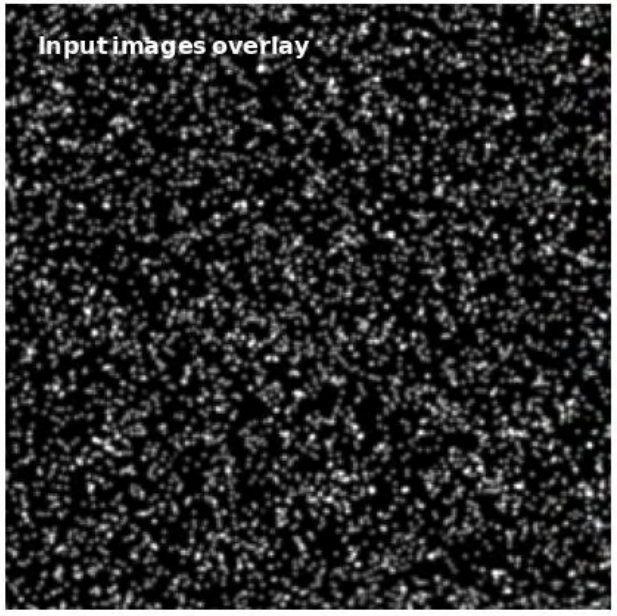


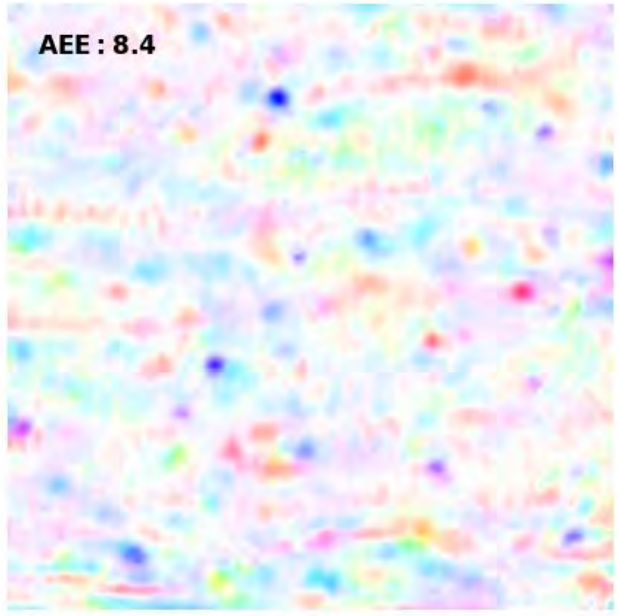


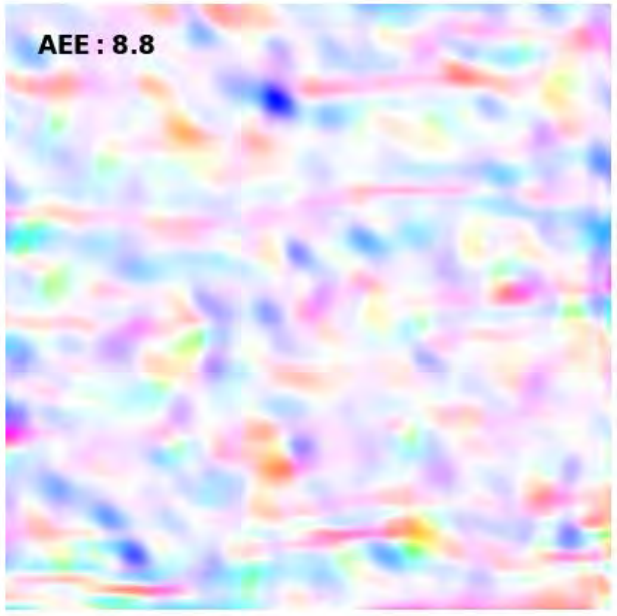
JHTDB
Channel











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