EUROVIS 2019

21ST EG/VGTC CONFERENCE ON VISUALIZATION

PORTO | PORTUGAL | 3-7 JUNE

Robust Reference Frame Extraction from Unsteady 2D Vector Fields with Convolutional Neural Networks

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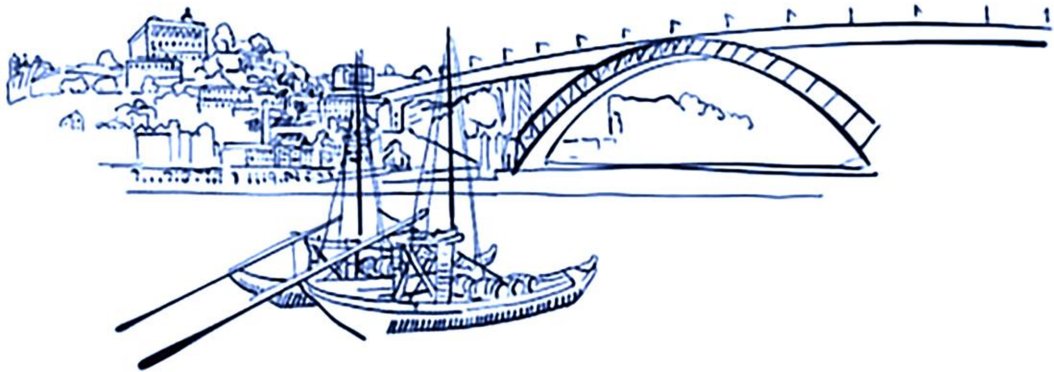
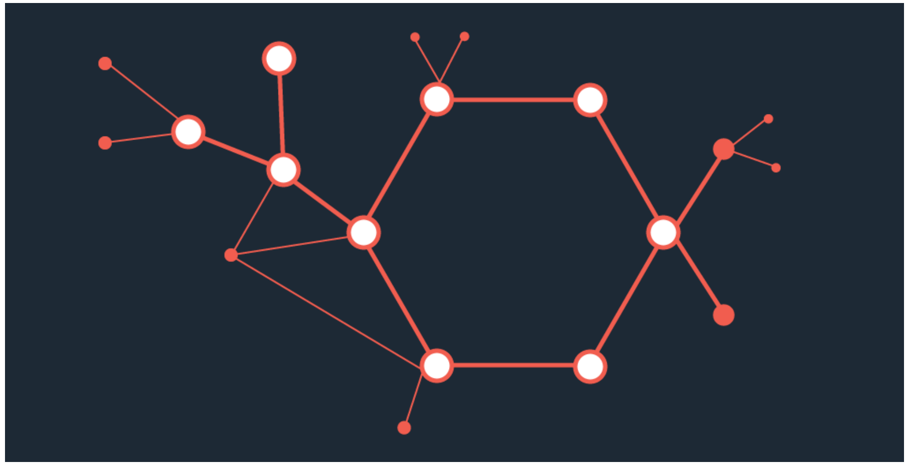


Visualization Process

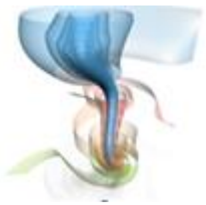
Preprocess → **Extraction** → **Mapping** → **Rendering**

01001110
01101111
01110010
01100001

Raw data



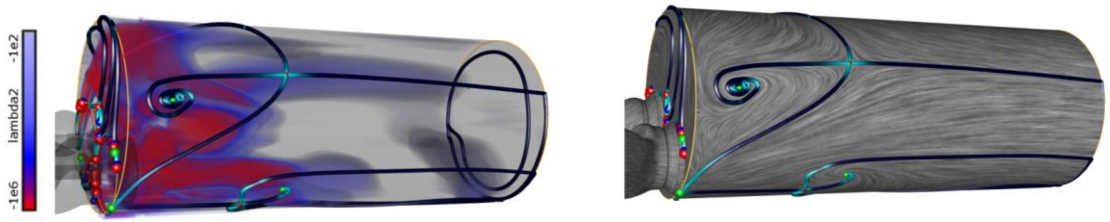
Deep Learning



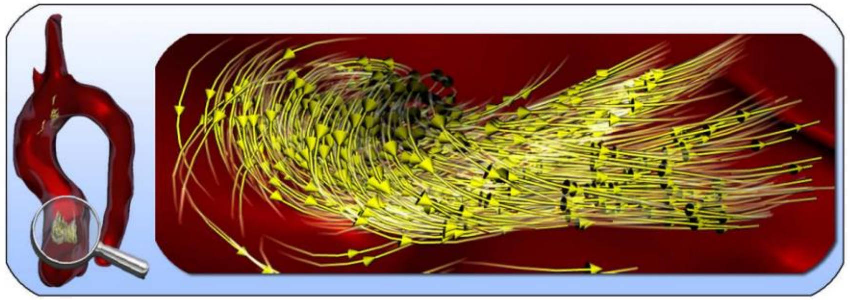
Image

Research in Vortices

Pitching Airfoil under Dynamic Stall
[Ouro et al., Journal of Fluids Engineering, 2018]



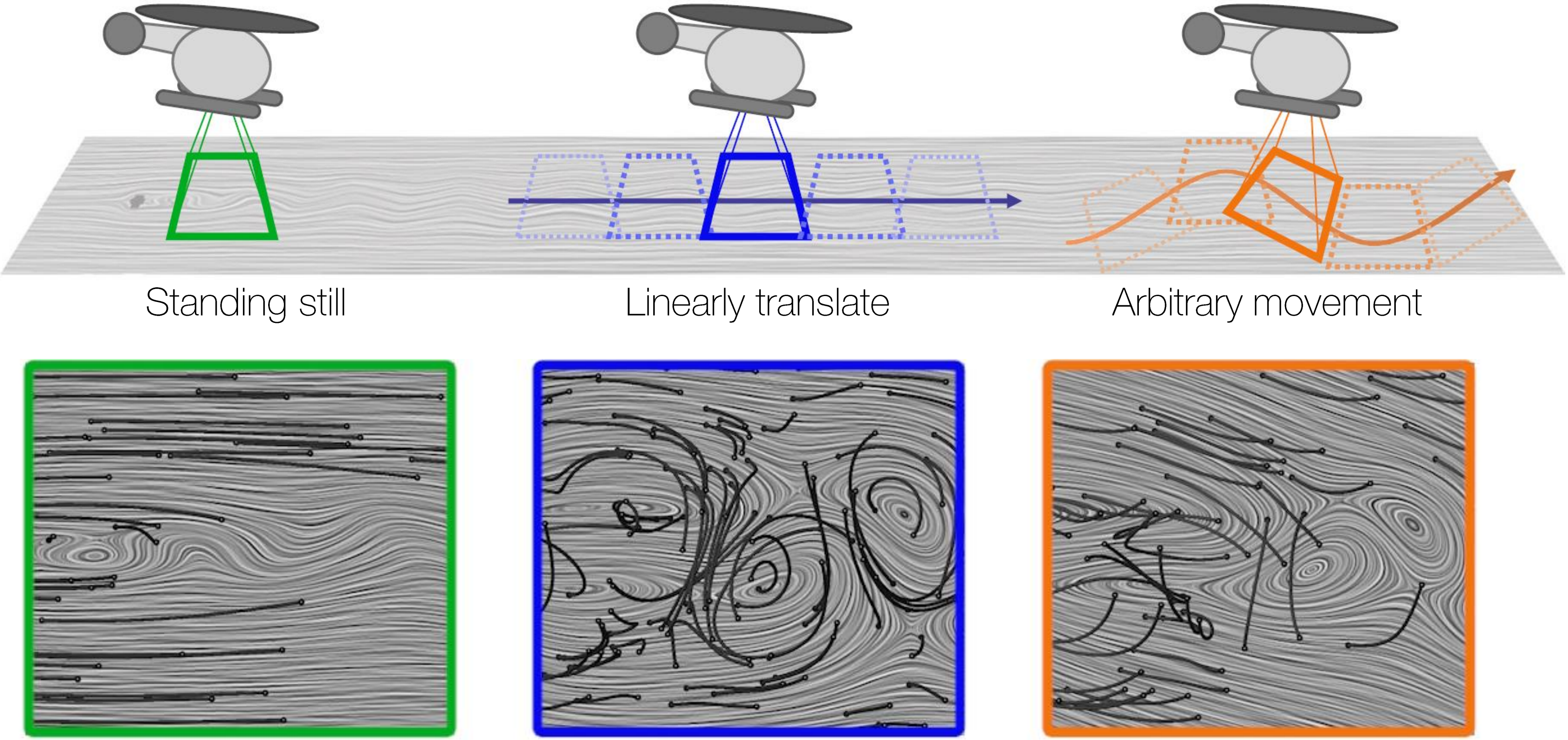
Engine Design
[Garth et al. 2007]



Blood Flow Analysis
[Köhler et al. 2013]

Extraction of Vortices

» **Reference Frames**

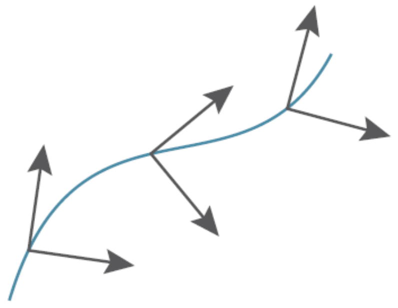


Result depends on the reference frame

[Slides from Günther and Theisel 2018]

Invariance to any smooth rotation and translation [Truesdell 1965]:

$$\mathbf{x}^* = \underbrace{\mathbf{Q}(t)}_{\text{time-dep. rotation}}\mathbf{x} + \underbrace{\mathbf{c}(t)}_{\text{time-dep. translation}}, \qquad t^* = t - a$$

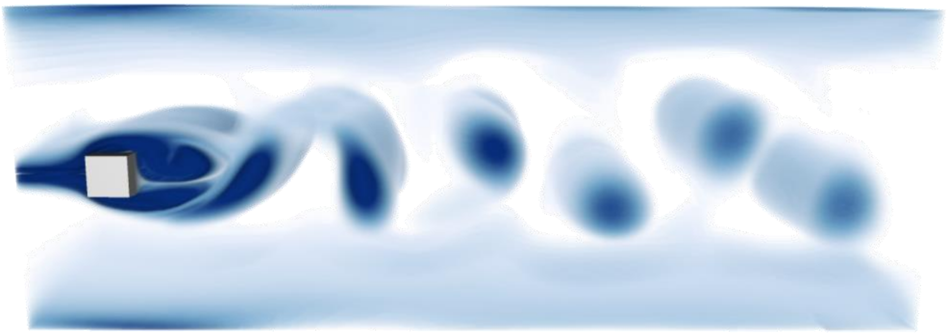


How to find vortices objectively?

Use Objective Differential Properties

Objective region-based measures:

- Relative vorticity [Drouot 1976, Tabor 1994]
- M_z Criterion [Haller 2005]
- IVD, LAVD [Haller 2016]



LAVD [Haller 2016]

Find Steady Reference Frame

[Lugt 1972, Robinson 1991]

Steady extractors apply:

- Critical points, Sujudi-Haimes

Optimization problem:

- Local [Günther and Theisel 2017,2018]
- Global [Hadwiger 2019]
- Deep Learning [this paper]

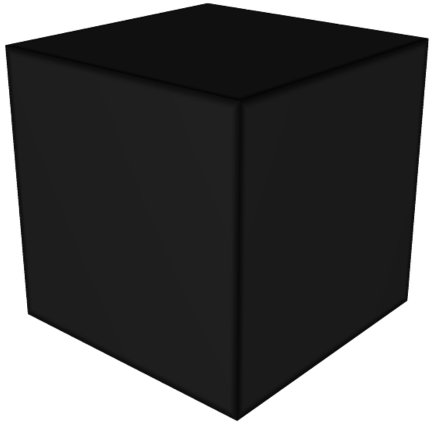
Optimization problem for the steady reference frame

- Given: unsteady vector field $\mathbf{v}(\mathbf{x}, t)$
- Unknown: reference frame transformation $\mathbf{x}^* = \mathbf{Q}(t)\,\mathbf{x} + \mathbf{c}(t)$
- Constraint: transformed field $\mathbf{v}^*$ is steady

$$\mathbf{v}_t^* \rightarrow \min$$

$$\mathbf{v}(\mathbf{x}, t)$$

Unsteady flow



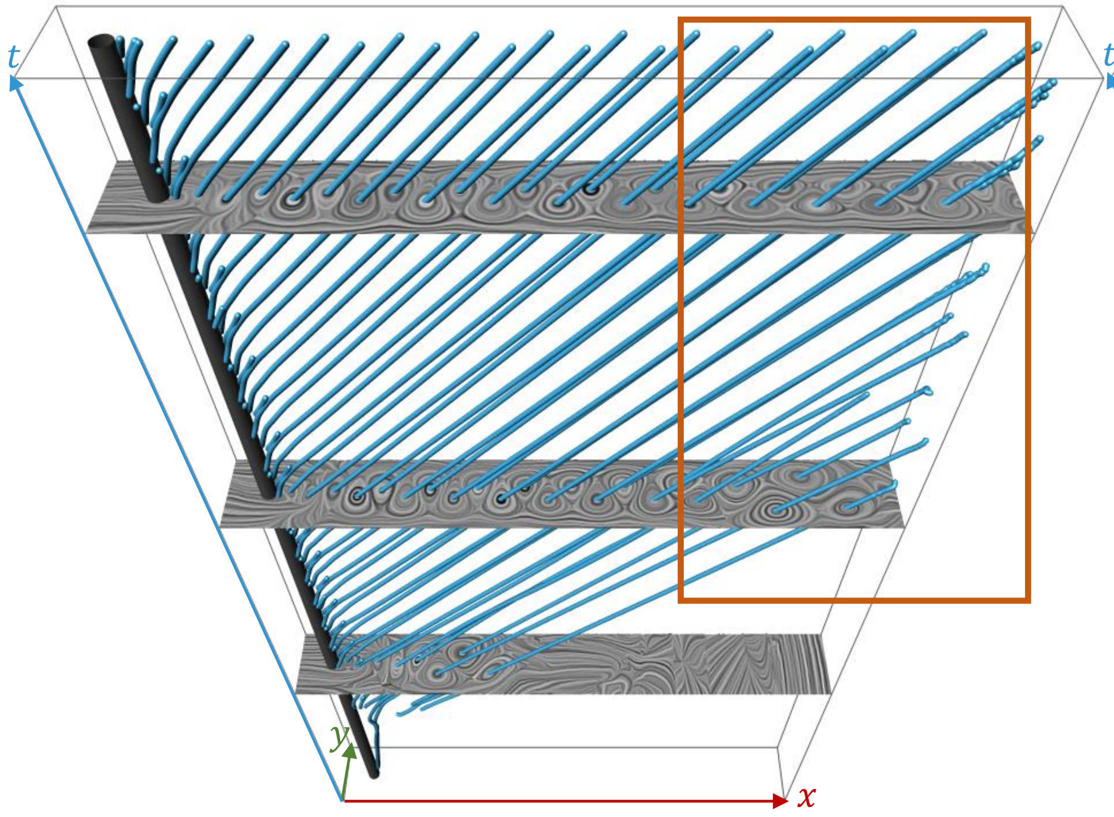
Difficult to find if data is noisy

$$\dot{\mathbf{Q}}, \ddot{\mathbf{Q}}, \dot{\mathbf{c}}, \ddot{\mathbf{c}}$$

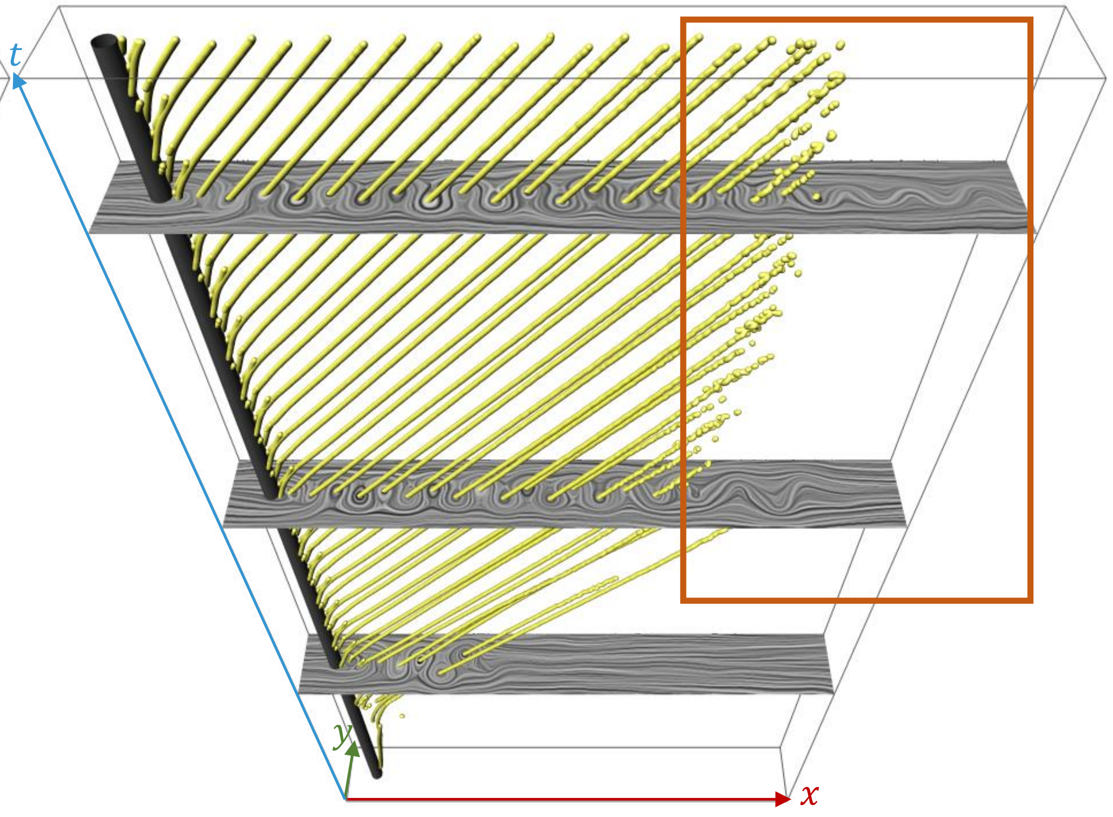
Parameters

Extraction of Vortices

» Optimal Reference Frames



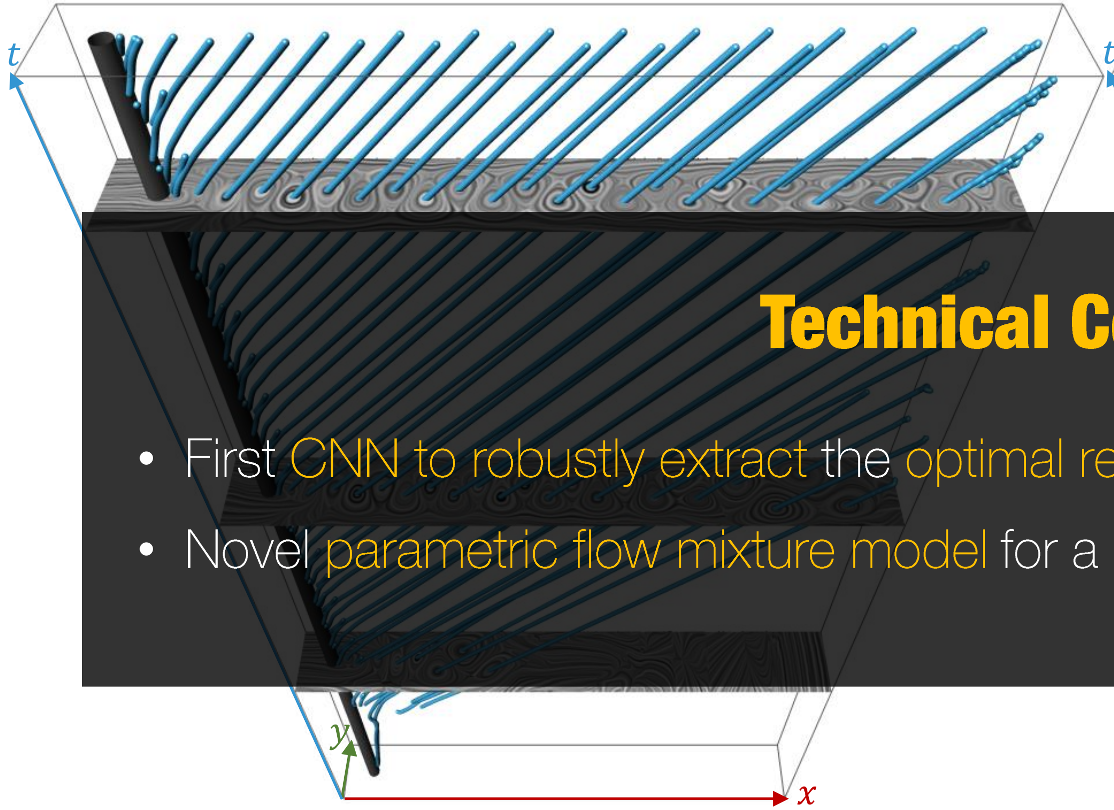
Linear Optimization on Original Data
[Günther et al. 2017]



Linear Optimization on Noisy Data

Technical Contributions

- First CNN to robustly extract the optimal reference frame of noisy unsteady flow
- Novel parametric flow mixture model for a large collection of vector field dataset



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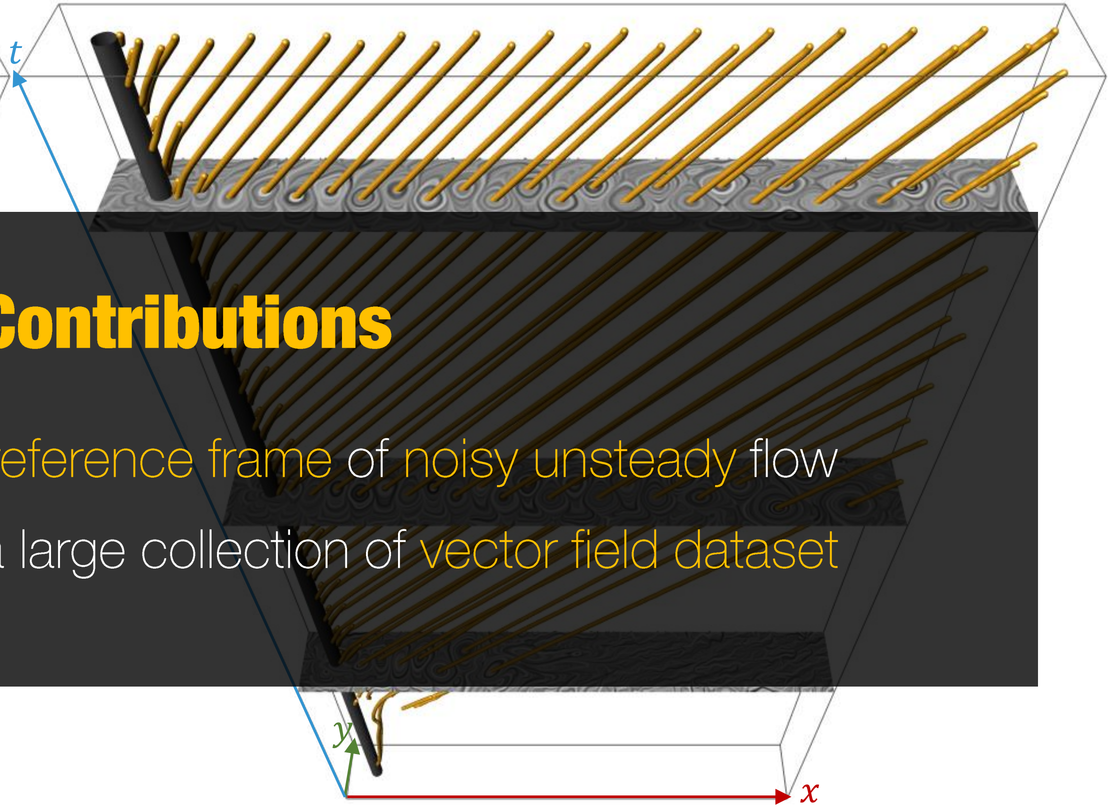
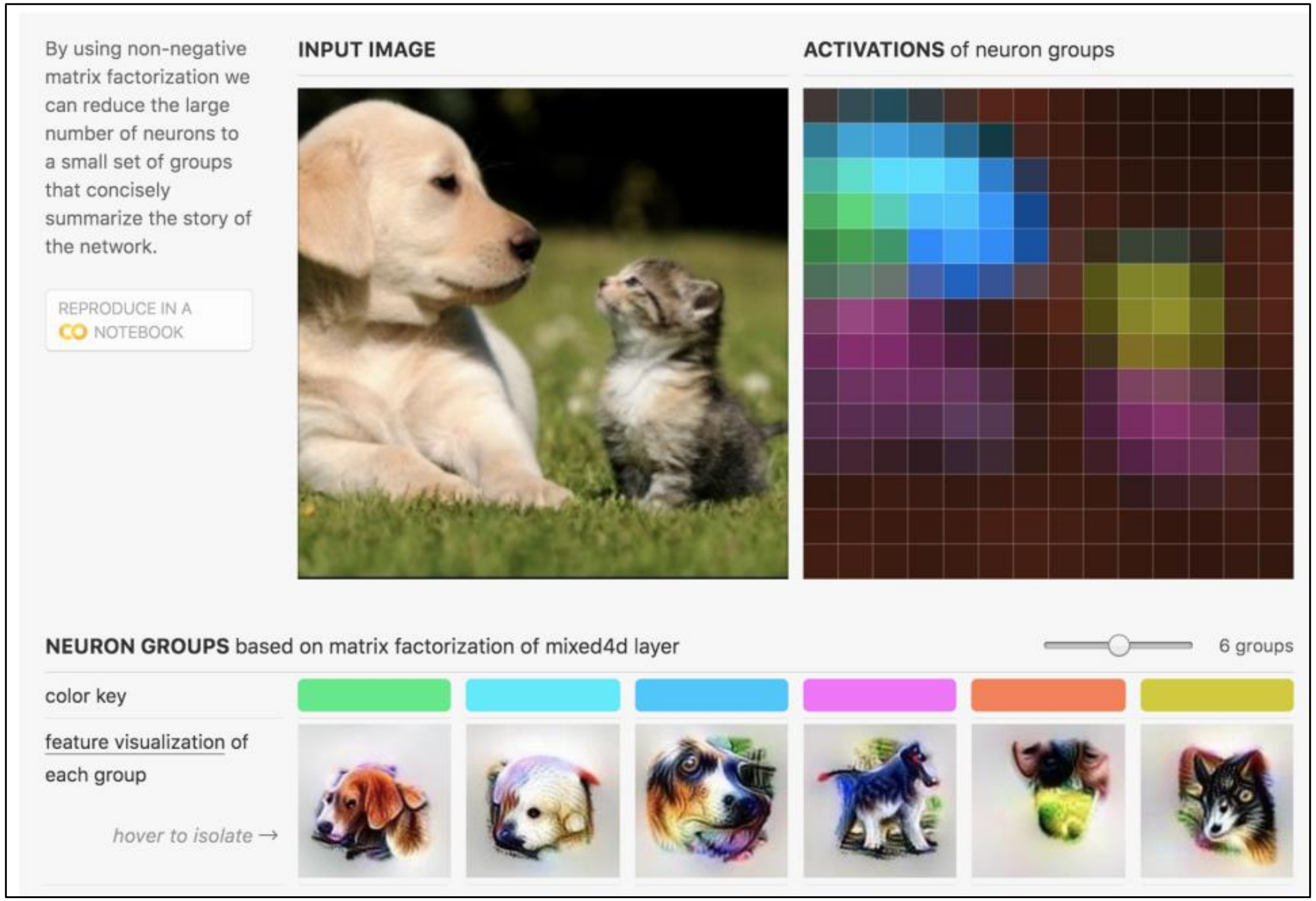


Our CNN-based approach on Noisy Data

Machine Learning Research in Visualization

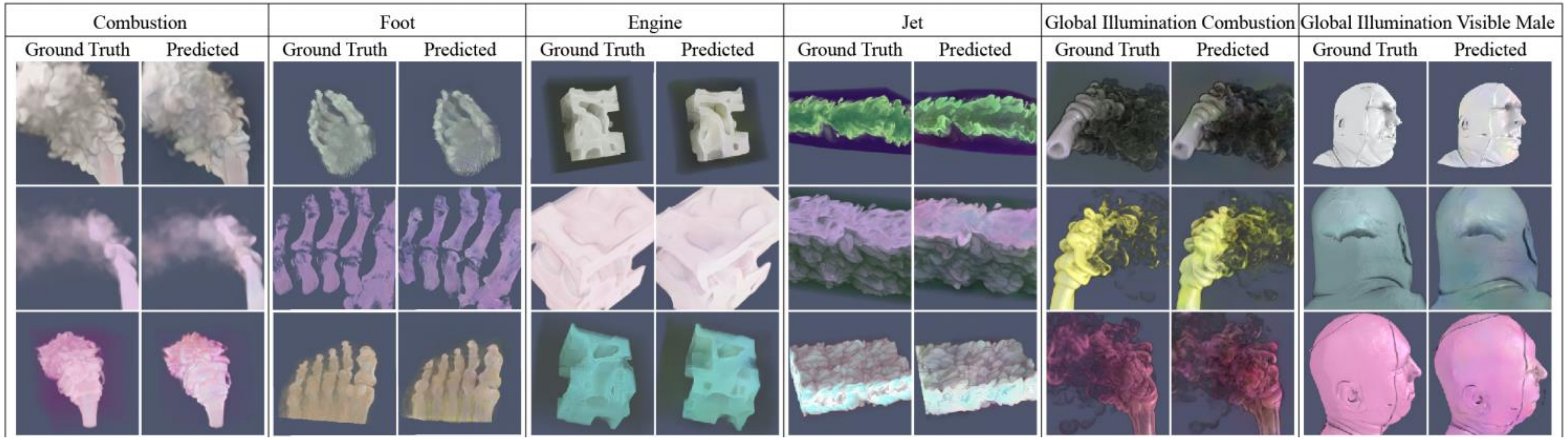
Explainable AI

» Black Box Visualization

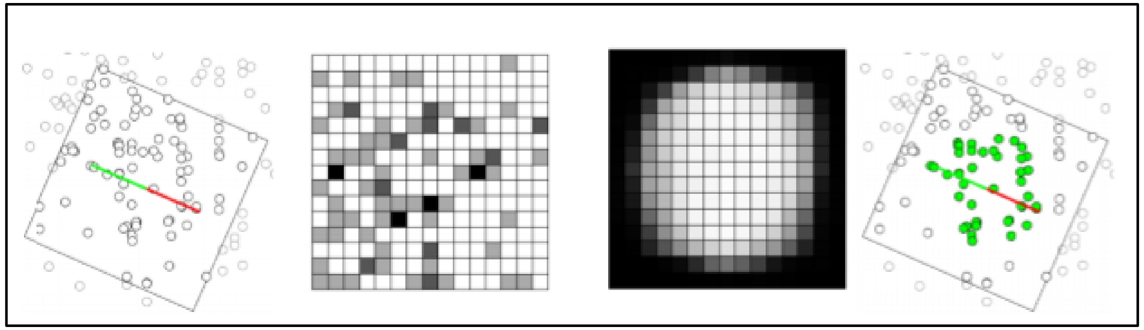


Interactive feature visualization to interpret neural networks [Olah et al. 2018]

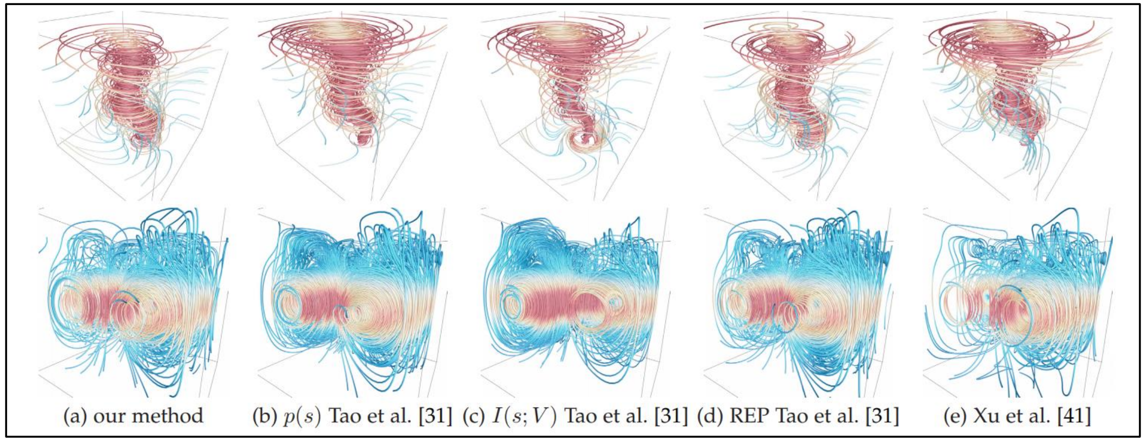
Deep Learning for Visualization



A Generative Model for Volume Rendering [Berger et al. 2017]

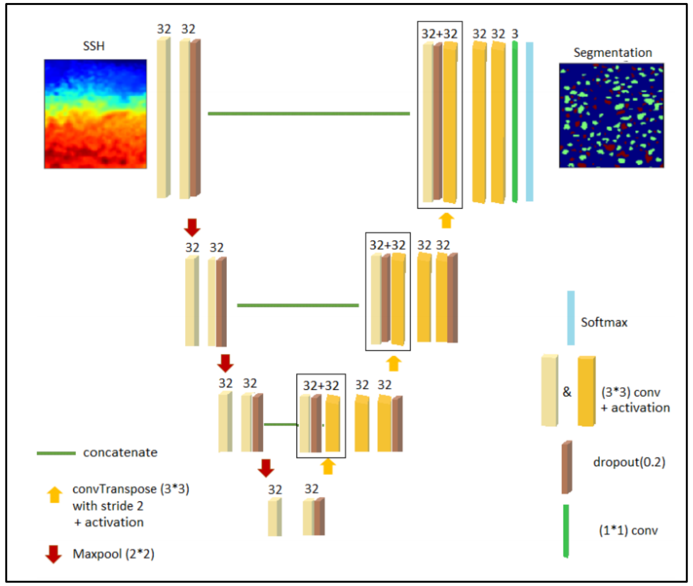


Fast & Accurate Brushing in Scatter Plots
[Fan and Hauser 2018]

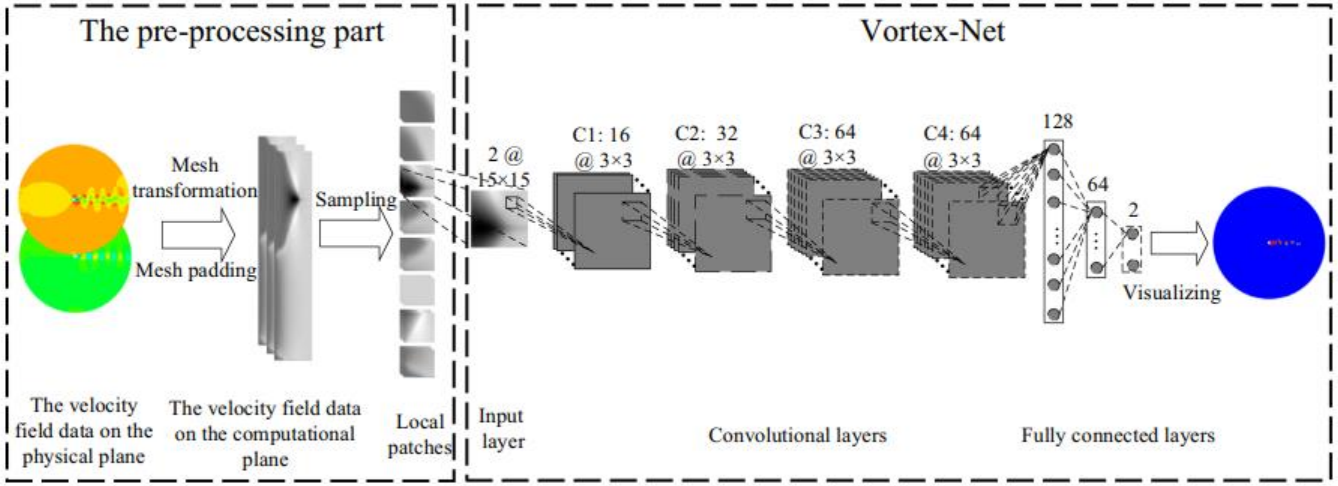


FlowNet [Han et al. 2018]

CNNs for Vortex Extraction



EddyNet [Lguensat et al. 2017]

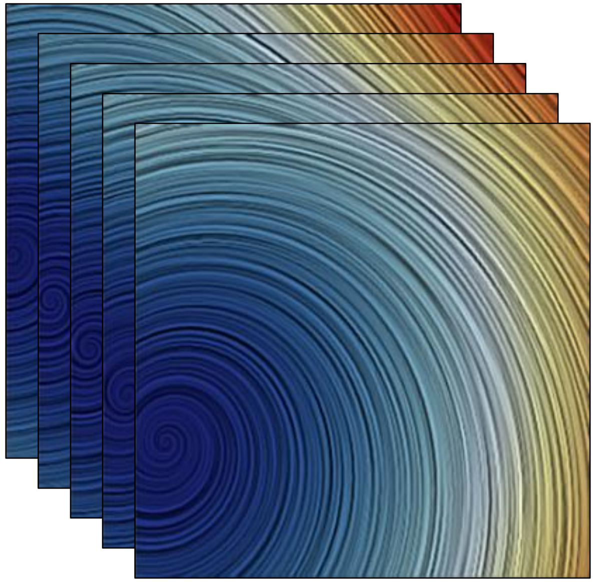


VortexNet [Deng et al. 2018]

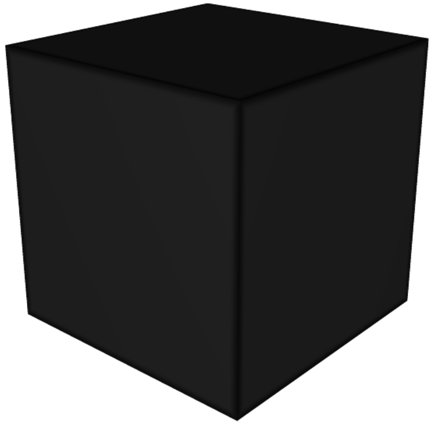
Overview

Deep Learning of Reference Frame Extraction

» Overview



Corrupted Unsteady Flow



$$\dot{\mathbf{Q}}, \ddot{\mathbf{Q}}, \dot{\mathbf{c}}, \ddot{\mathbf{c}}$$

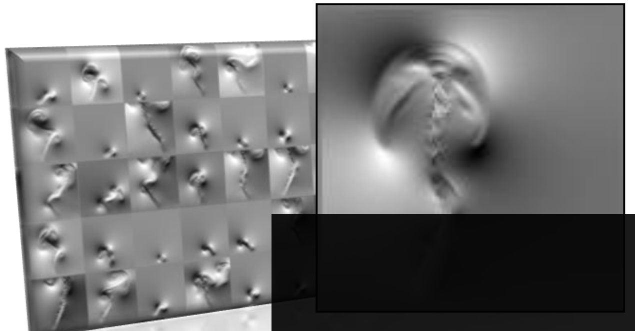
Parameters

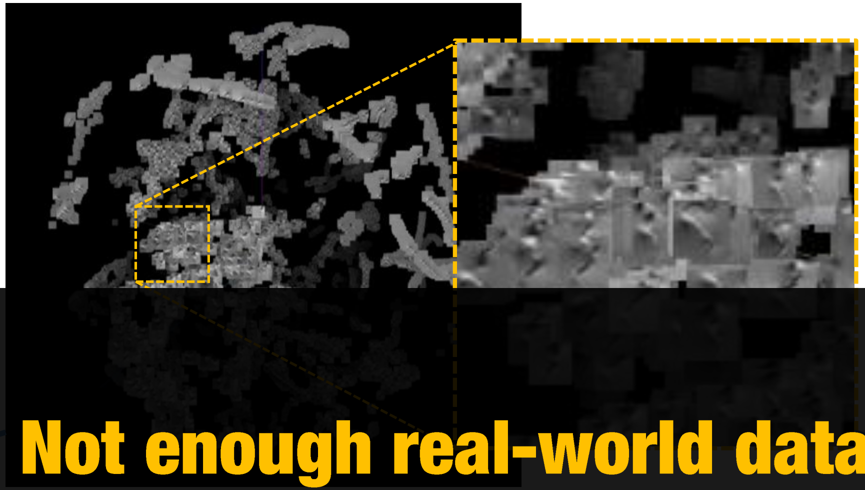
1. Synthesize a steady flow
2. Transform to unsteady flows
3. Degenerate with noise and resampling artifacts
4. Supervised learning

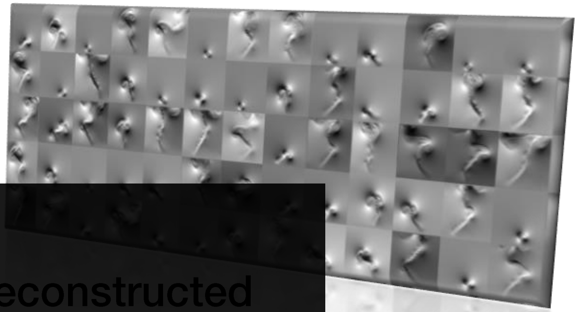
Synthetic Generation of Vector Fields

Parametric Mixture Model for Vector Fields

» Learning a Fluid Data Manifold







Not enough real-world data

Need constraints for physically-plausible flows

Dimensionality Reduction for Manifold Learning

Linear: PCA, SVD, ICA, Factor Analysis, etc.

Nonlinear: Auto-Encoder, GAN, LLE, Laplacian Eigenmaps, etc.

[Slide from Kim et al. 2018]

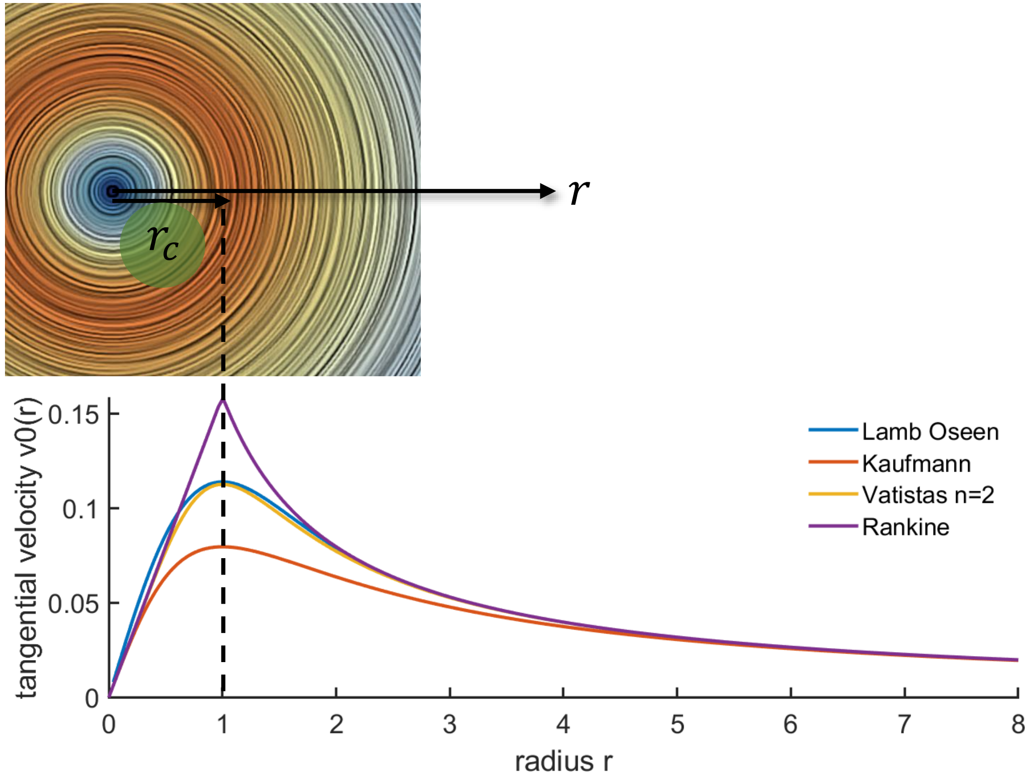
Vatistas Vortex Velocity Profile [Vatistas et al. 1991]

- Tangential flow velocity of a rotationally-symmetric unit vortex

$$v_0(r) = \frac{r}{2\pi r_c^2 \left(\left(\frac{r}{r_c} \right)^{2n} + 1 \right)^{\frac{1}{n}}}$$

radius with maximal velocity

shape exponent



8-Dimensional Parametric Model for a Steady Flow Primitive

$$\mathbf{v}_p(x,y) = \begin{bmatrix} d_x & c_x \\ -c_y & d_y \end{bmatrix} \begin{pmatrix} x - t_x \\ y - t_y \end{pmatrix} \frac{v_0\left(\sqrt{(x-t_x)^2 + (y-t_y)^2}\right)}{\sqrt{(x-t_x)^2 + (y-t_y)^2}}$$

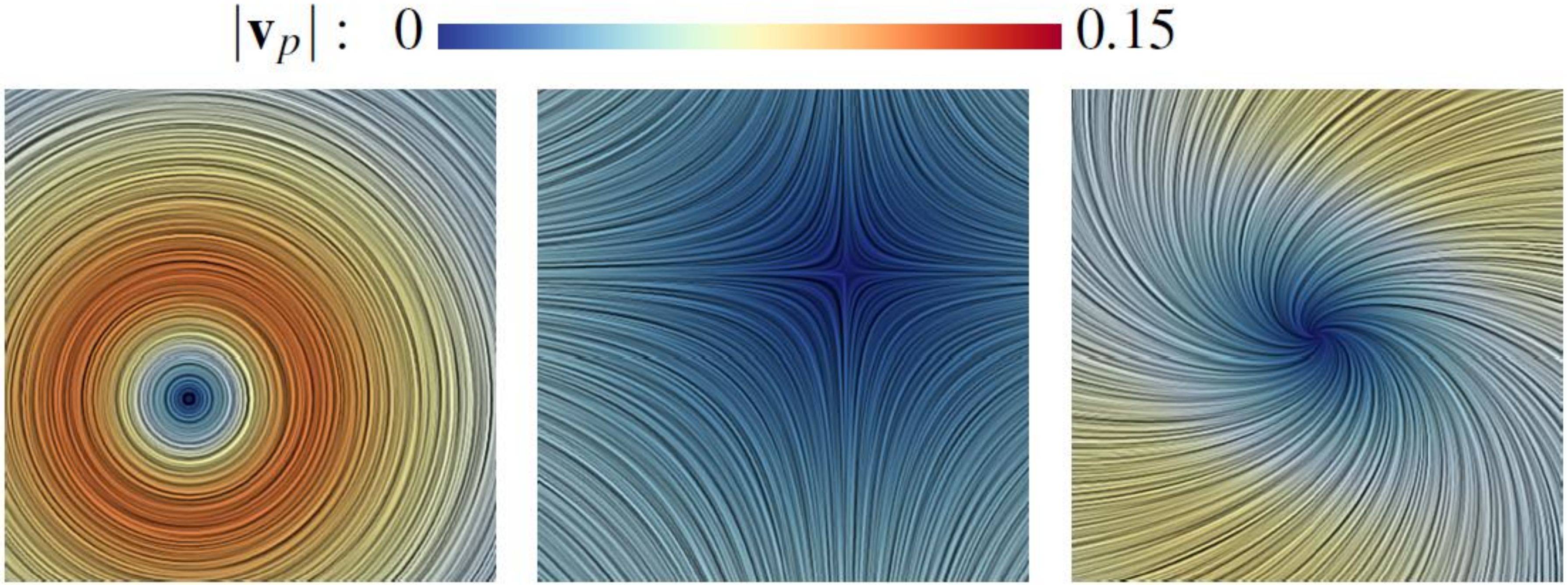
vortical motion

divergence

critical point

Parametric Mixture Model for Vector Fields

» Example of 2D Steady Flows from Our Model



$\mathbf{c} = (1,1)$, $\mathbf{d} = (0,0)$, $\mathbf{t} = (-\frac{1}{2}, -\frac{1}{2})$, $r_c = 1$, $n = 2$

$\mathbf{c} = (0,0)$, $\mathbf{d} = (1,-1)$, $\mathbf{t} = (\frac{1}{2}, \frac{1}{2})$, $r_c = 3$, $n = 8$

$\mathbf{c} = (1, \frac{1}{2})$, $\mathbf{d} = (1,1)$, $\mathbf{t} = (0,0)$, $r_c = 2$, $n = 2$

Parametric Mixture Model for Vector Fields

» Parameter Space Fitting

$$\mathbf{v}(x,y) = \sum_{p=1}^{m} \mathbf{v}_p(x,y)$$

A mixture model of m flow primitives

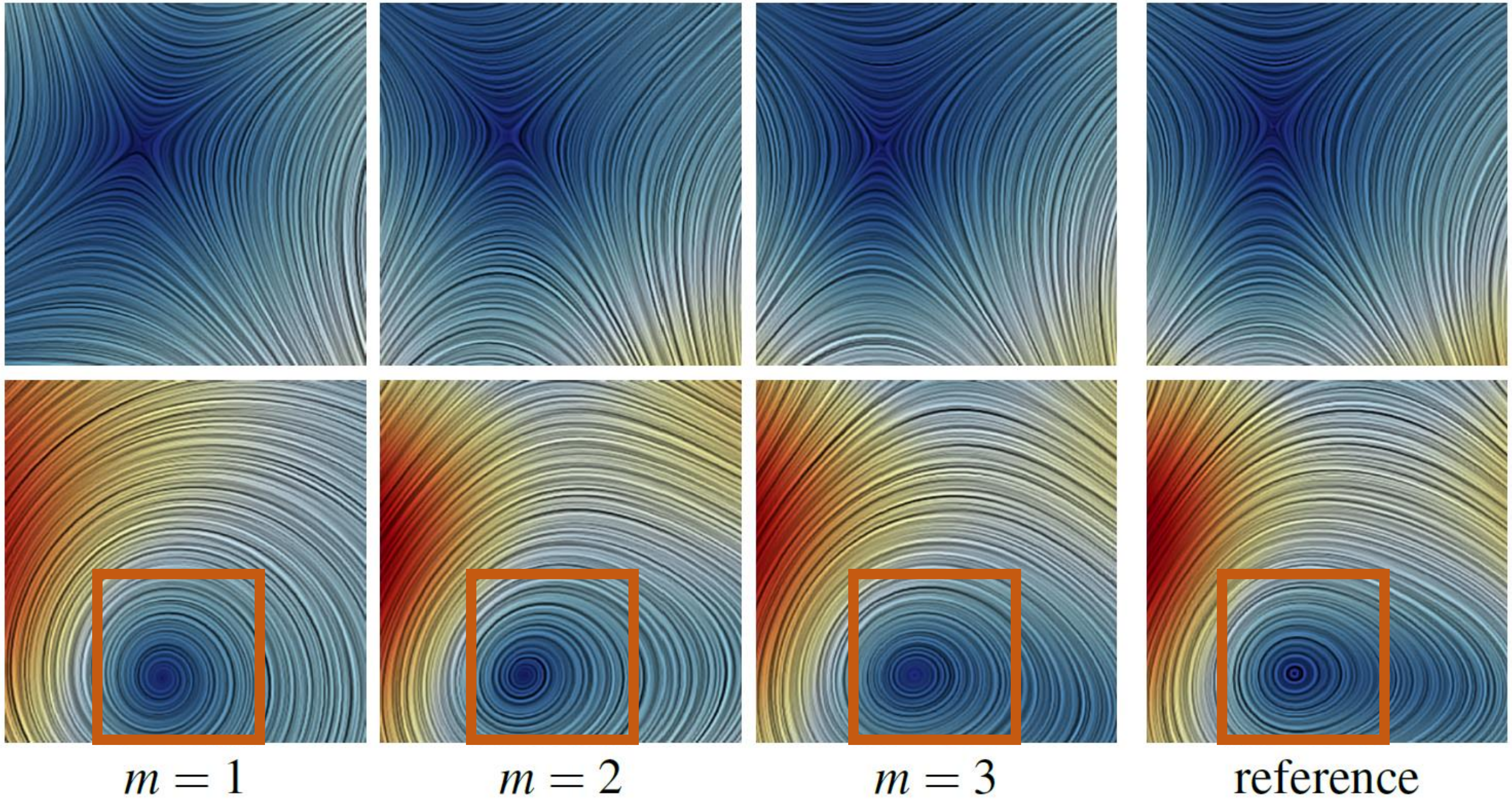
How can we restrict the parameter space to physically-plausible flows?

Parameter Space Fitting!

- Extract optimal reference frame
- Simulated annealing + Gradient Descent
- $\mathcal{L}(\hat{\mathbf{v}}, \mathbf{v}) = ||\hat{\mathbf{v}} - \mathbf{v}||_1 + \lambda||\nabla\hat{\mathbf{v}} - \nabla\mathbf{v}||_1$ [Kim et al. 2018]

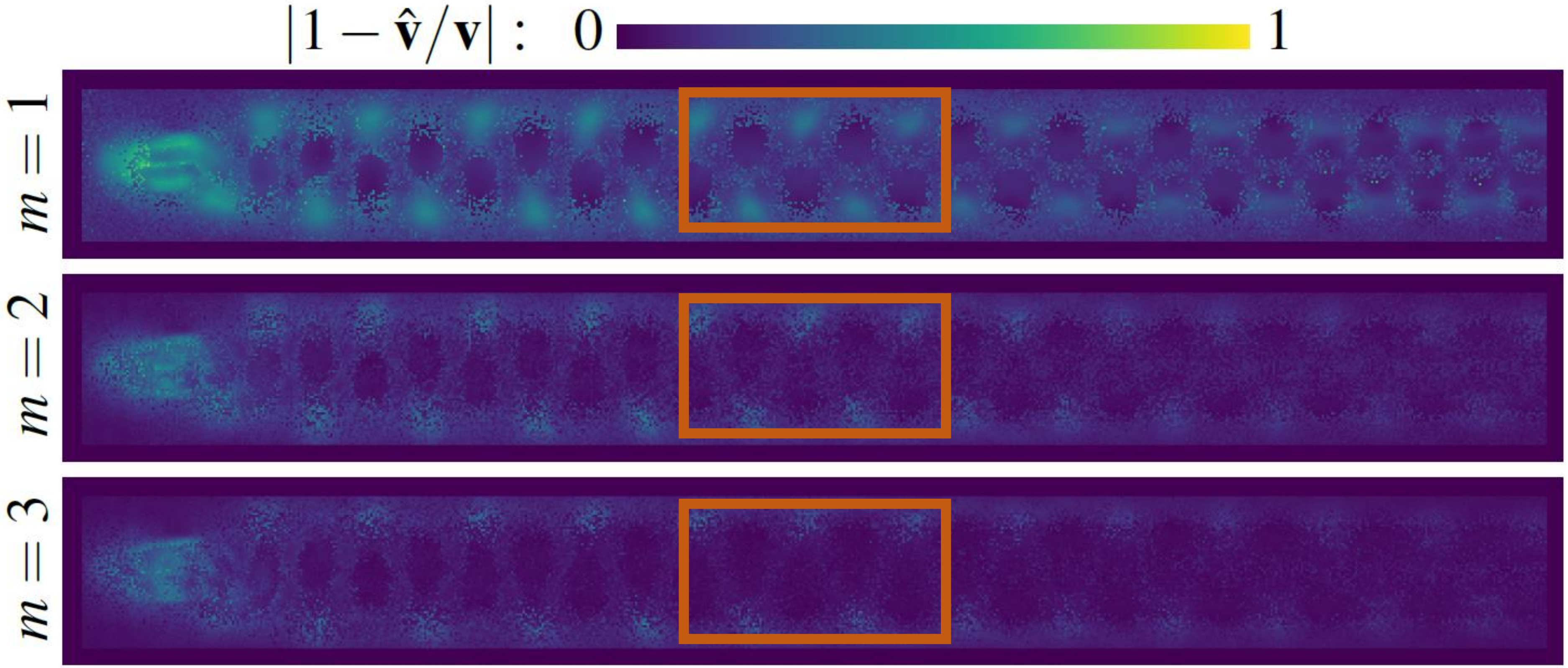
Parametric Mixture Model for Vector Fields

» Fitting Results for Selected Vector Field Patches



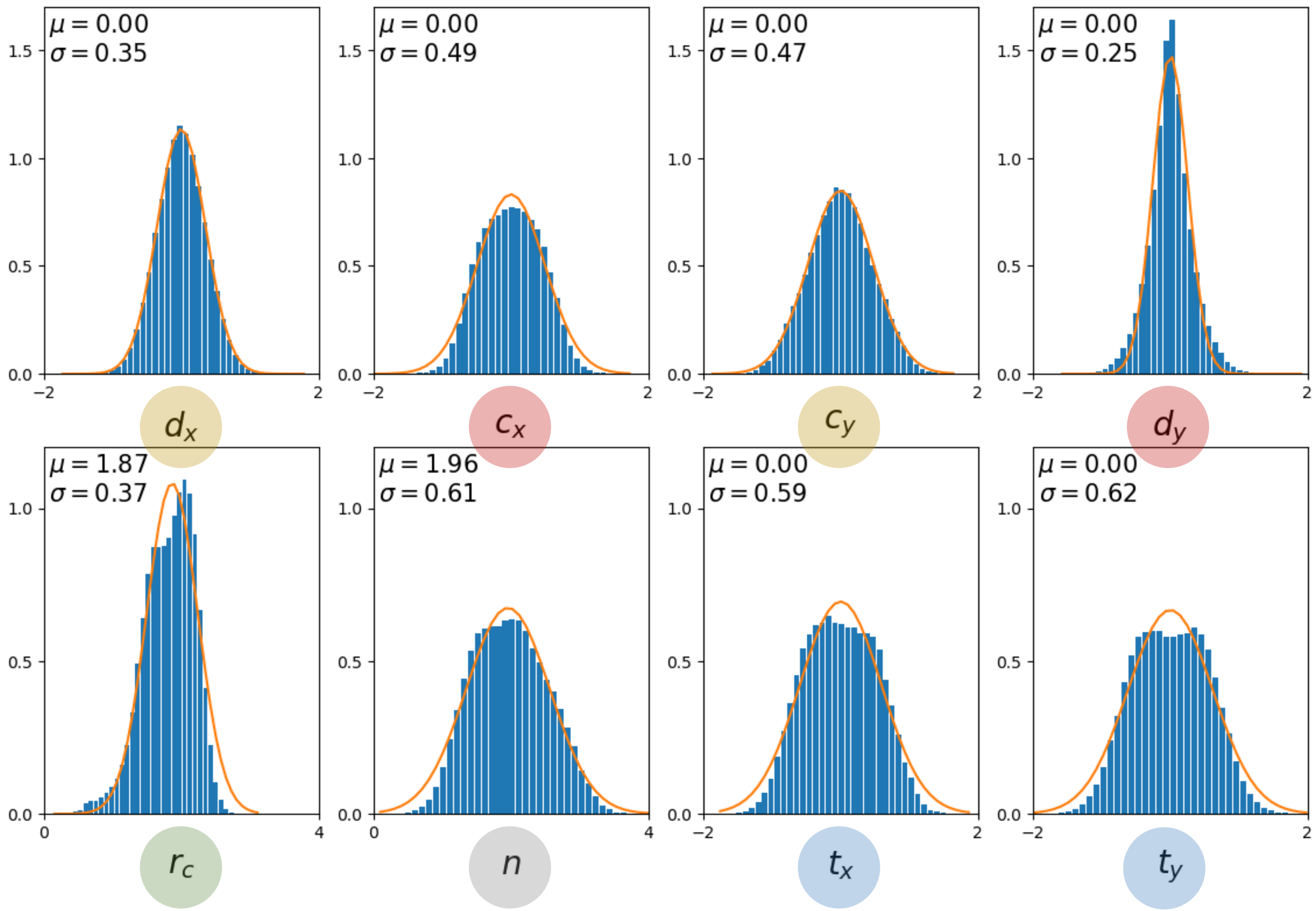
Parametric Mixture Model for Vector Fields

» Heat Maps of the Fitting Residual



Parametric Mixture Model for Vector Fields

» **Histograms of the Individual Model Parameters**

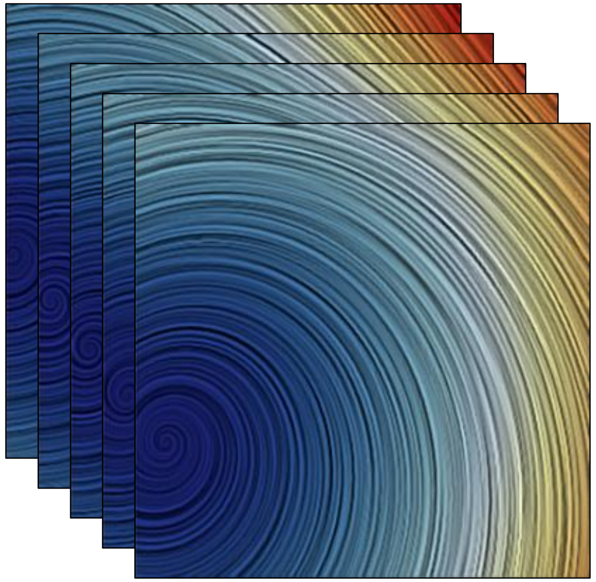


Allows sampling for further steady vector field patches

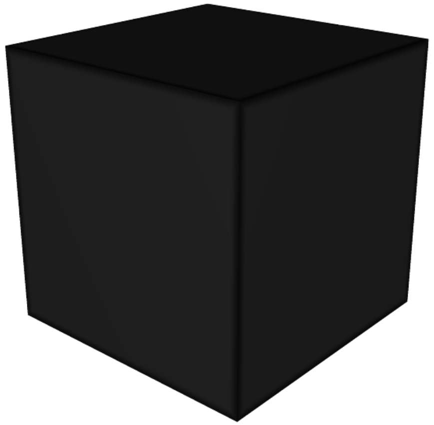
Deep Learning of Reference Frame Extraction

Deep Learning of Reference Frame Extraction

» Overview



Corrupted Unsteady Flow



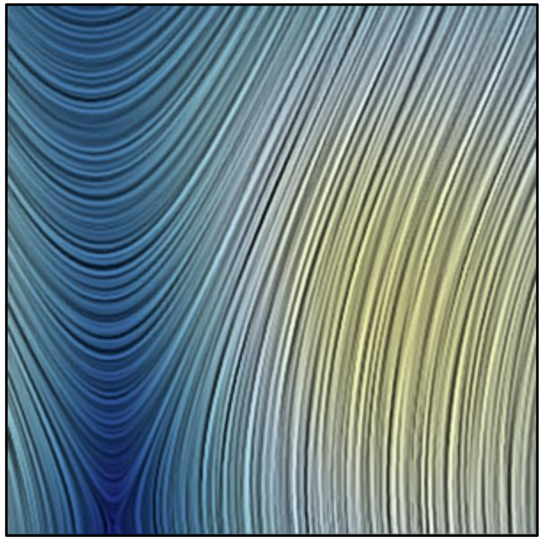
$$\dot{\mathbf{Q}}, \ddot{\mathbf{Q}}, \dot{\mathbf{c}}, \ddot{\mathbf{c}}$$

Parameters

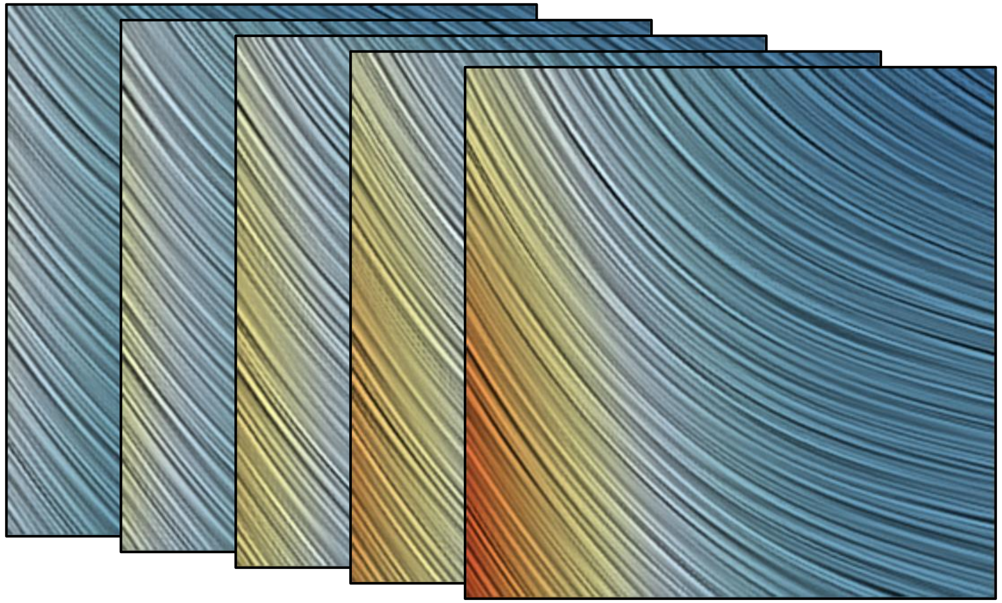
1. Synthesize a steady flow
2. Transform to unsteady flows
3. Degenerate with noise and resampling artifacts
4. Supervised learning

Deep Learning of Reference Frame Extraction

» Dataset



Steady Field $\mathbf{v}$ from a Mixture Model



Unsteady Fields $\mathbf{v}^*$

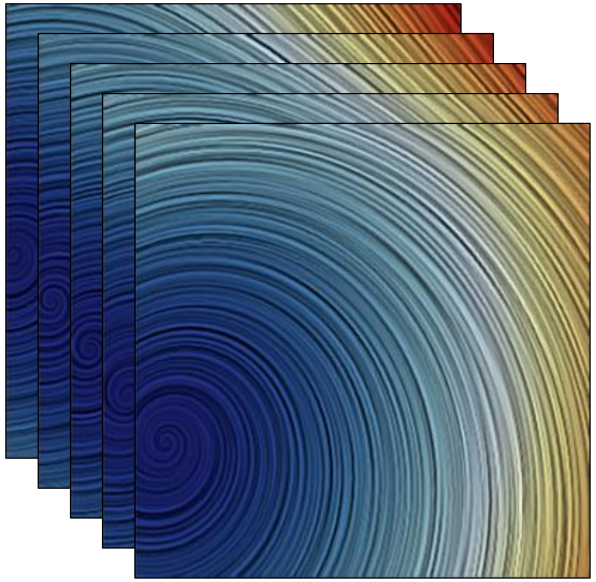
Transformation:

$$\mathbf{v}^*(\mathbf{x}^*, t^*) = \mathbf{Q}(t)\mathbf{v}(\mathbf{x}, t) + \dot{\mathbf{Q}}(t)\mathbf{x} + \dot{\mathbf{c}}(t)$$

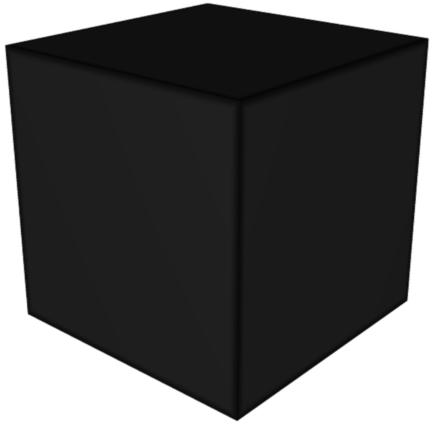
$$\mathbf{x} = \mathbf{Q}(t)^{\mathrm{T}}\left(\mathbf{x}^* - \mathbf{c}(t)\right), \qquad t = t^* + a$$

Deep Learning of Reference Frame Extraction

» Overview



Corrupted Unsteady Flow



$$\dot{\mathbf{Q}}, \ddot{\mathbf{Q}}, \dot{\mathbf{c}}, \ddot{\mathbf{c}}$$

Parameters

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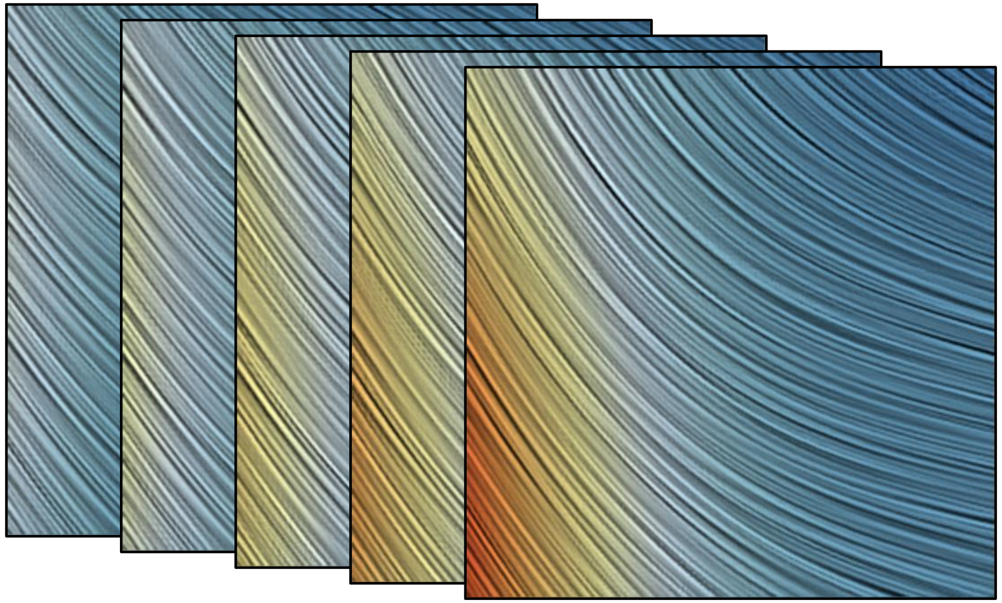
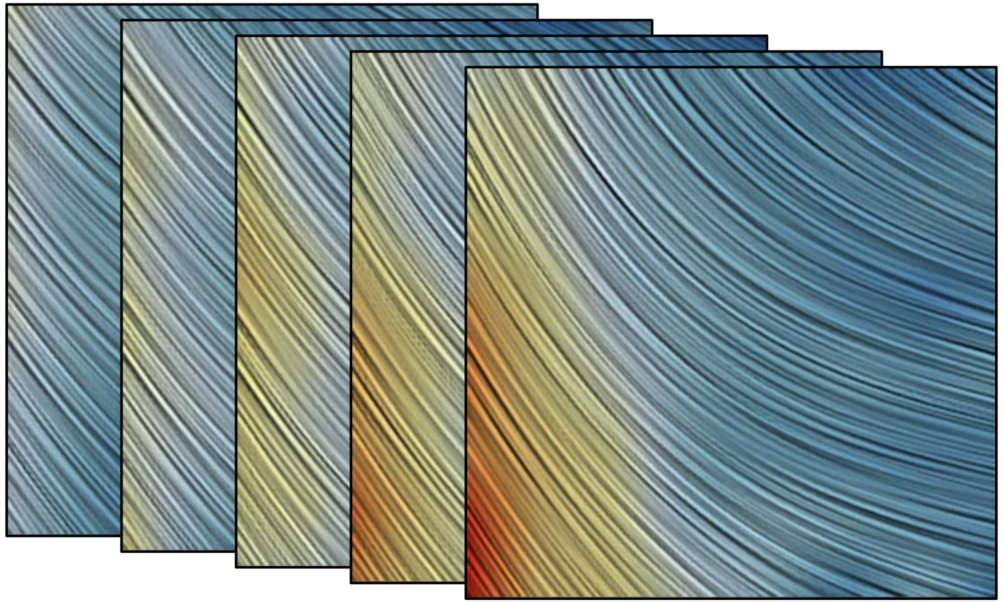
Deep Learning of Reference Frame Extraction

» **Dataset**



Unsteady Fields



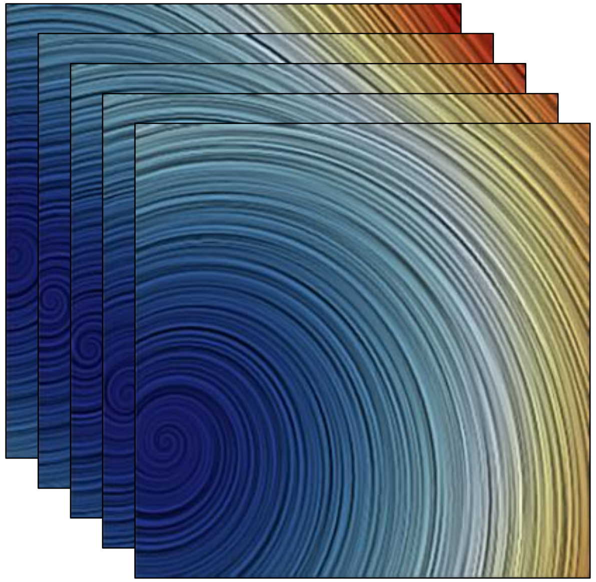
Degenerated Unsteady Fields

Degeneration

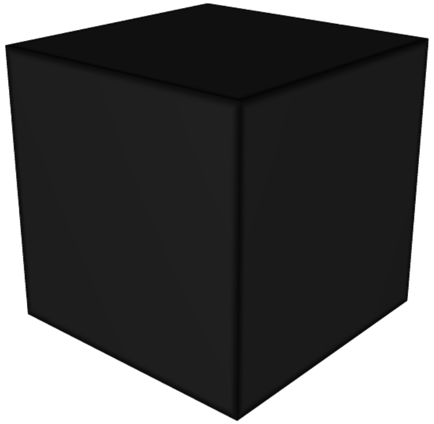
- Additive uniform noise
- Down-up resampling as distortion artifacts

Deep Learning of Reference Frame Extraction

» Overview



Corrupted Unsteady Flow



$\dot{\mathbf{Q}}, \ddot{\mathbf{Q}}, \dot{\mathbf{c}}, \ddot{\mathbf{c}}$

Parameters

1. Synthesize a steady flow
2. Transform to unsteady flows
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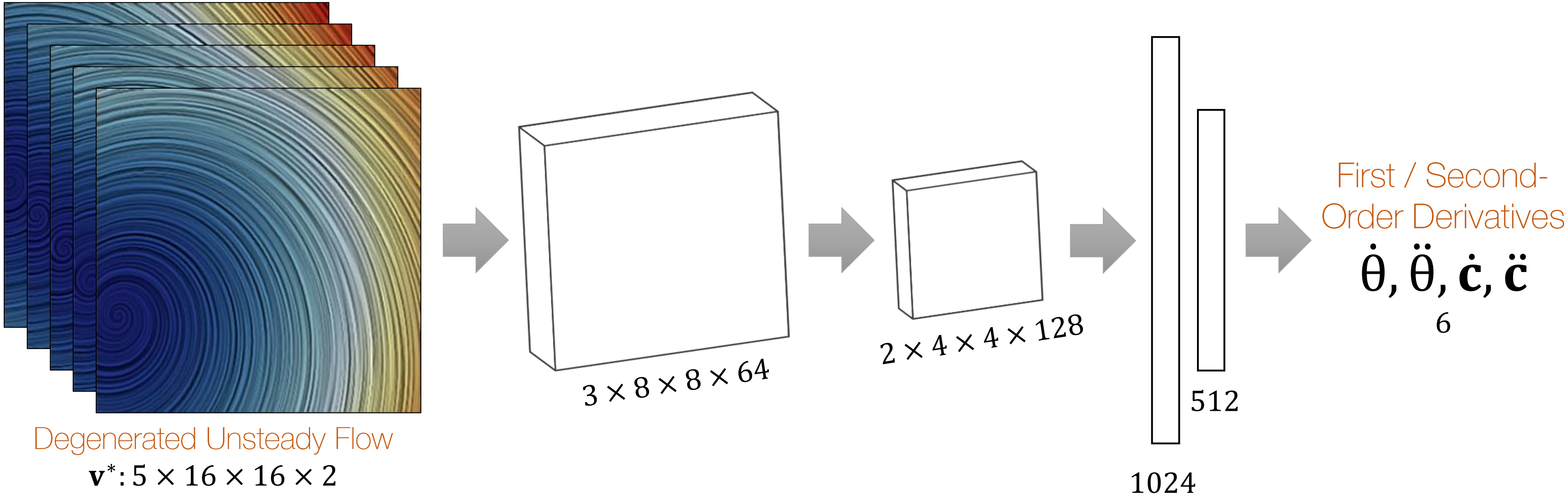
Deep Learning of Reference Frame Extraction

» Architecture



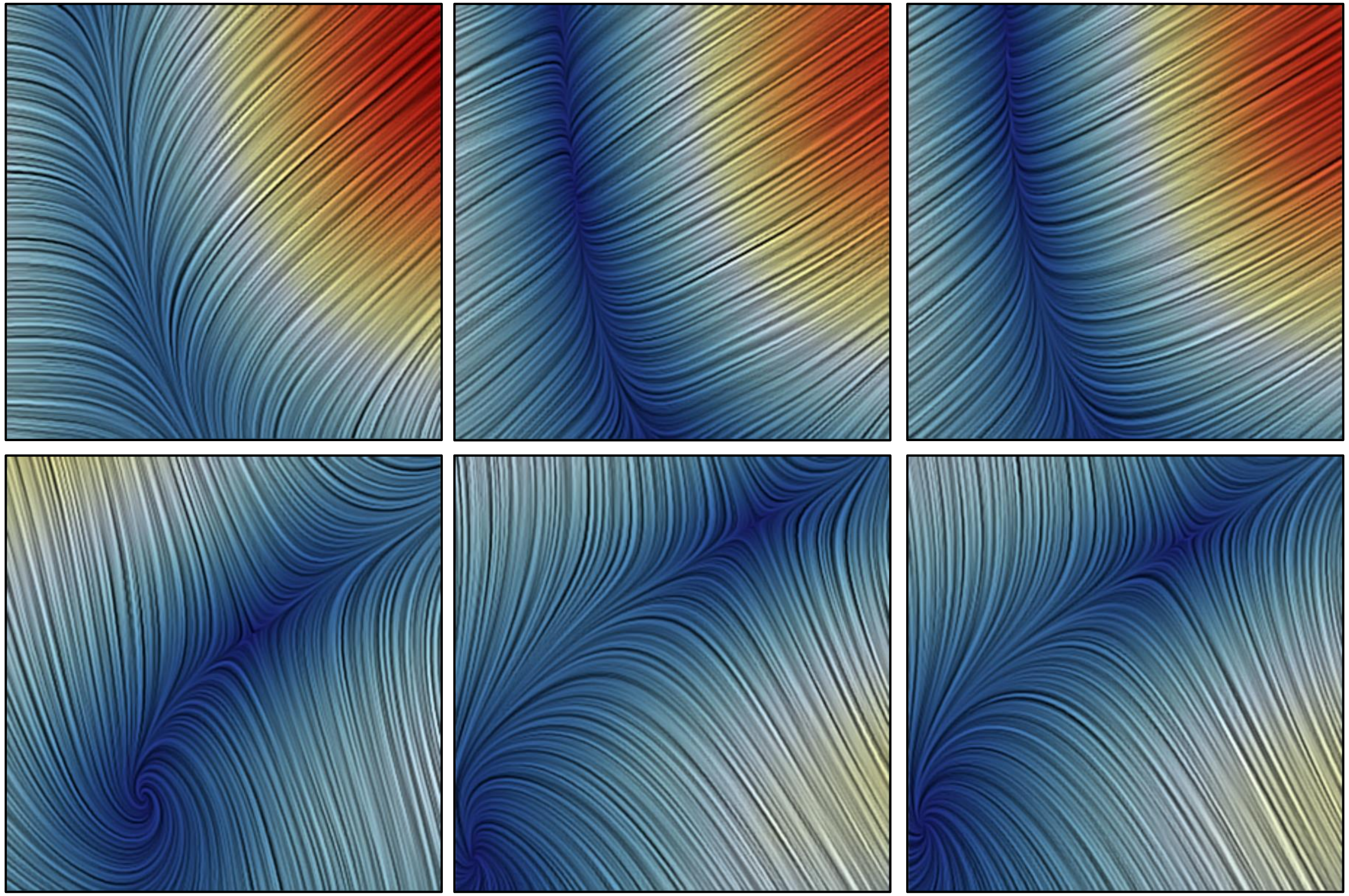
Architecture

- 3D convolutional kernels for feature extraction
- Followed by batch normalization and ReLU layer
- MLP for the final inference

Result

Result

» Vortex Extraction on Test Splits



Linear opt. (1.09e-2) Ours (2.13e-4) Ground Truth

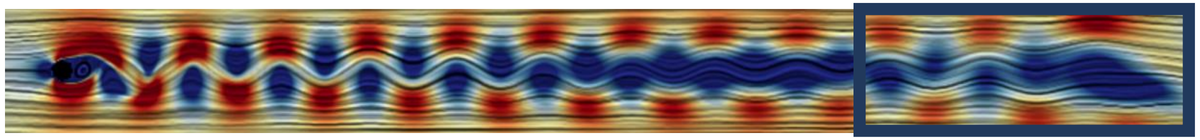
Result

» **Validation on Numerical Data**

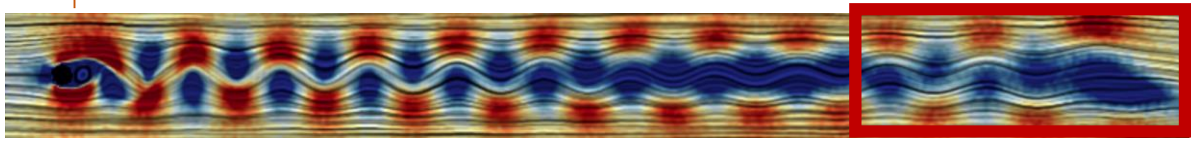
Cylinder flow

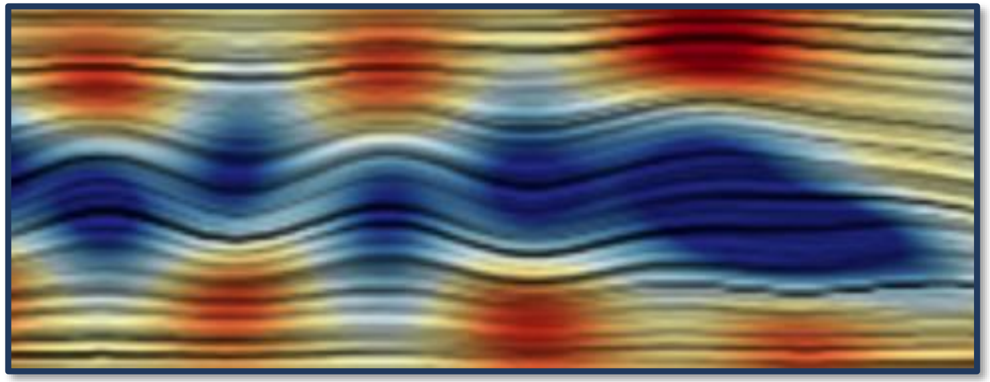
- Resolution: $640 \times 80 \times 5$
- Window size: $16 \times 16 \times 5$
  - Stride: 1, Batch size: 256
  - 159 steps for 40,625 windows

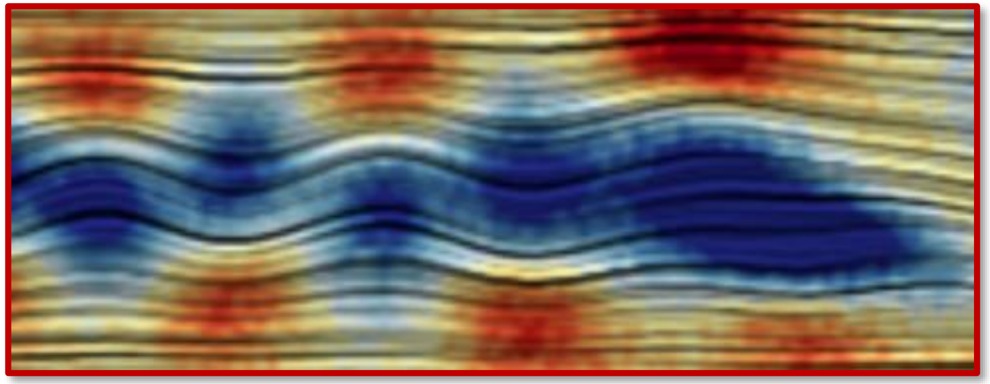
Original Data



Impaired Data

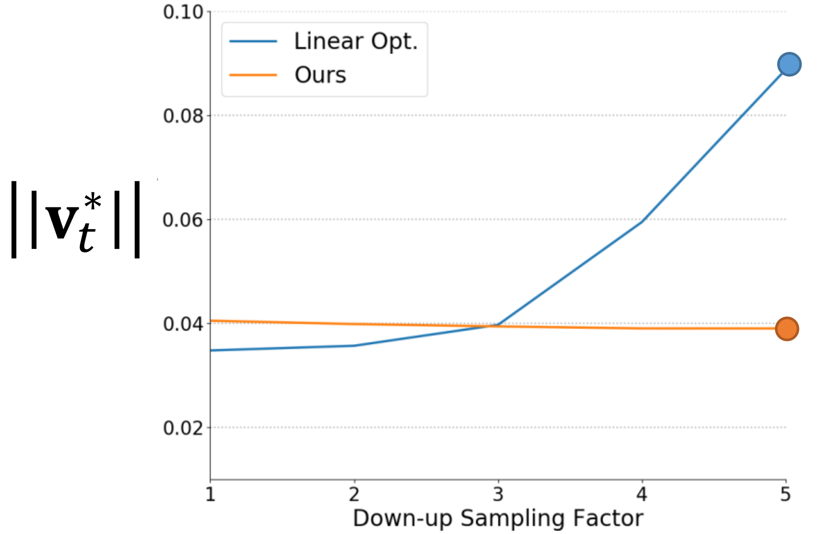


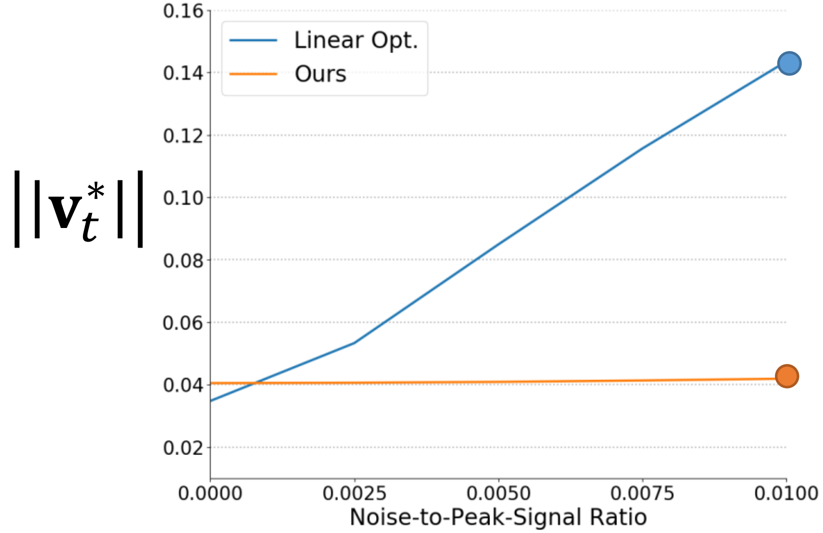


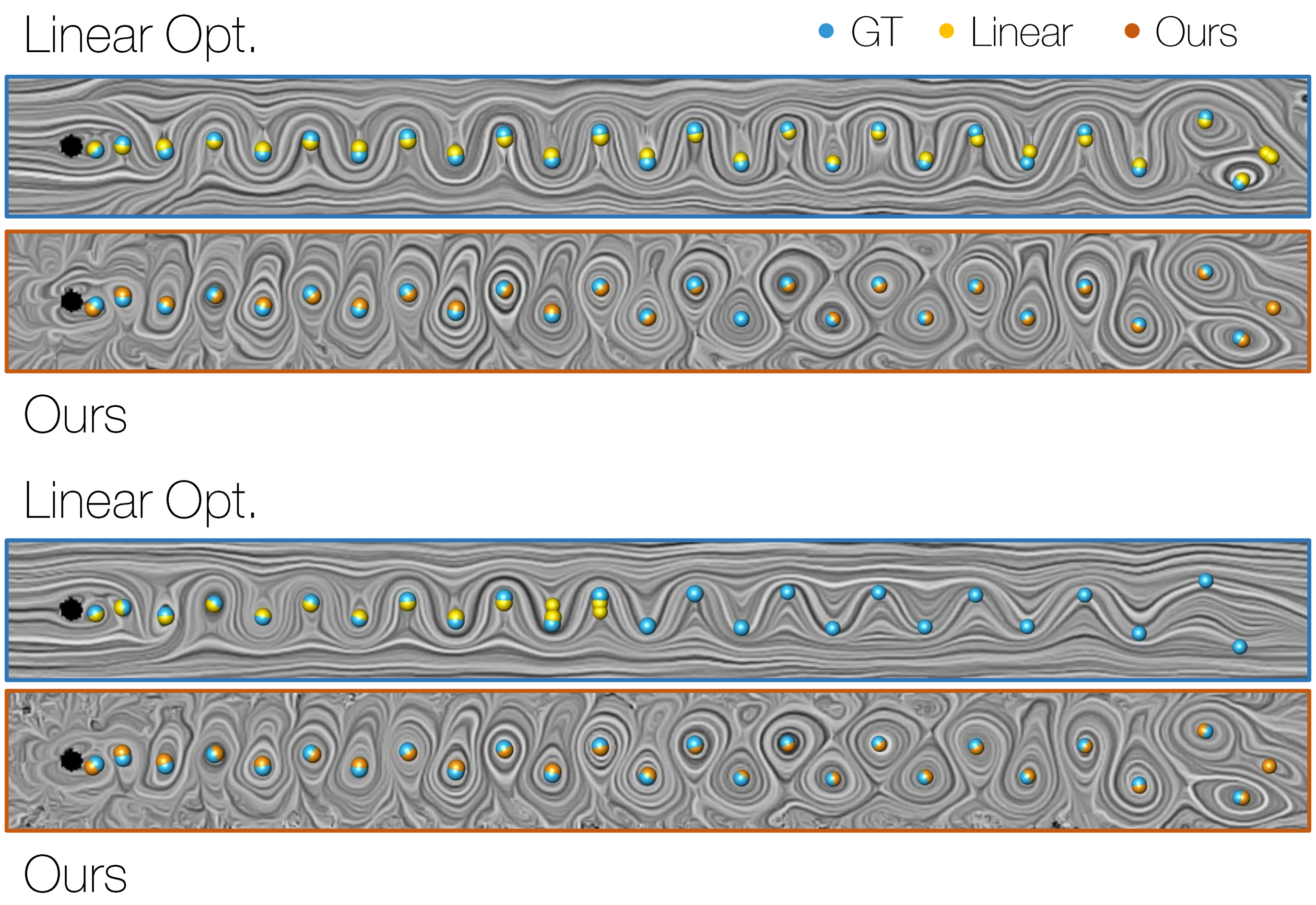


Result

» Validation on Numerical Data



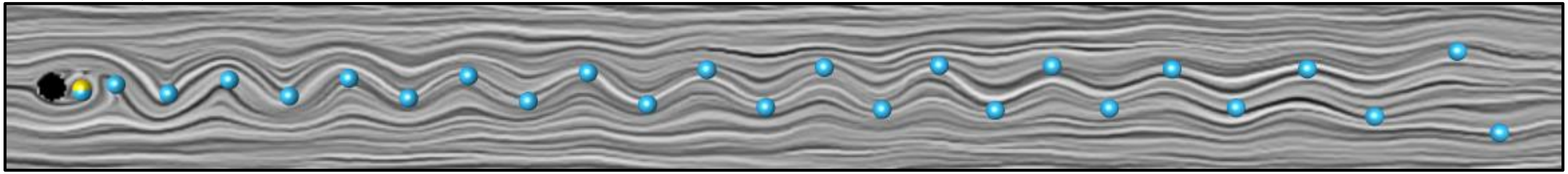




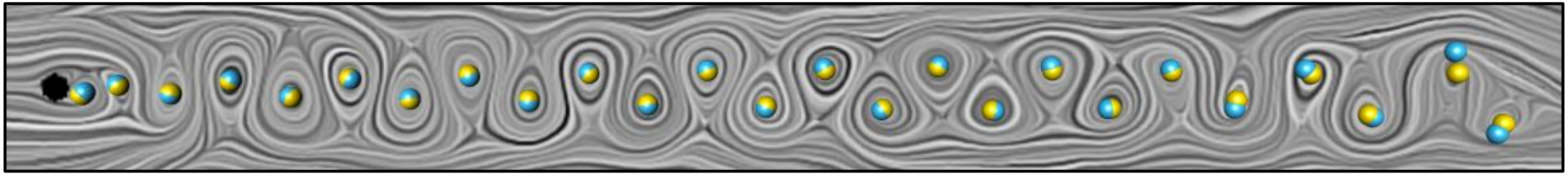
Result

» **Validation on Numerical Data**

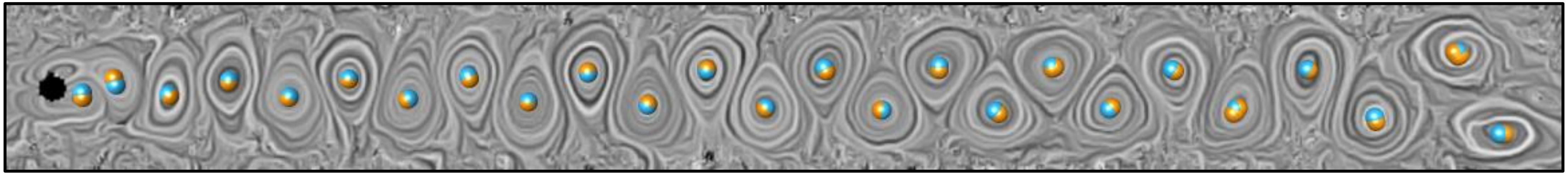
Linear Opt. on noise 10%



Linear Opt. after gaussian smoothing (7x7)

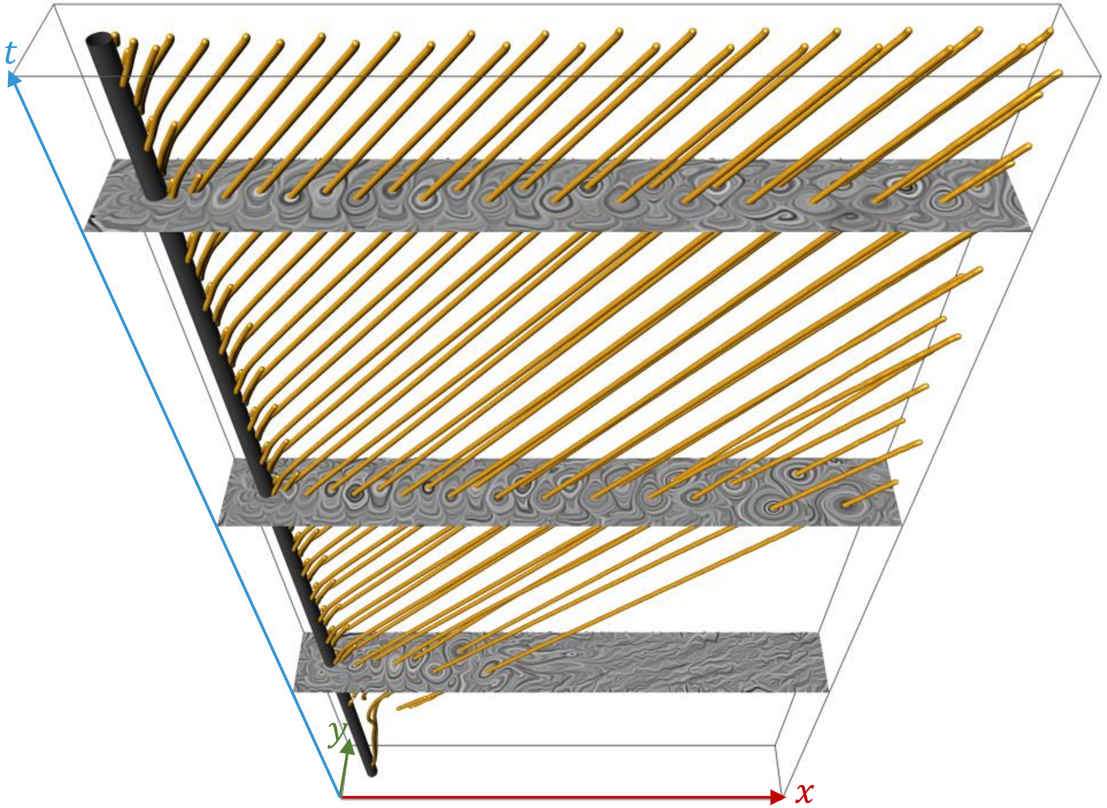


Ours



Limitation

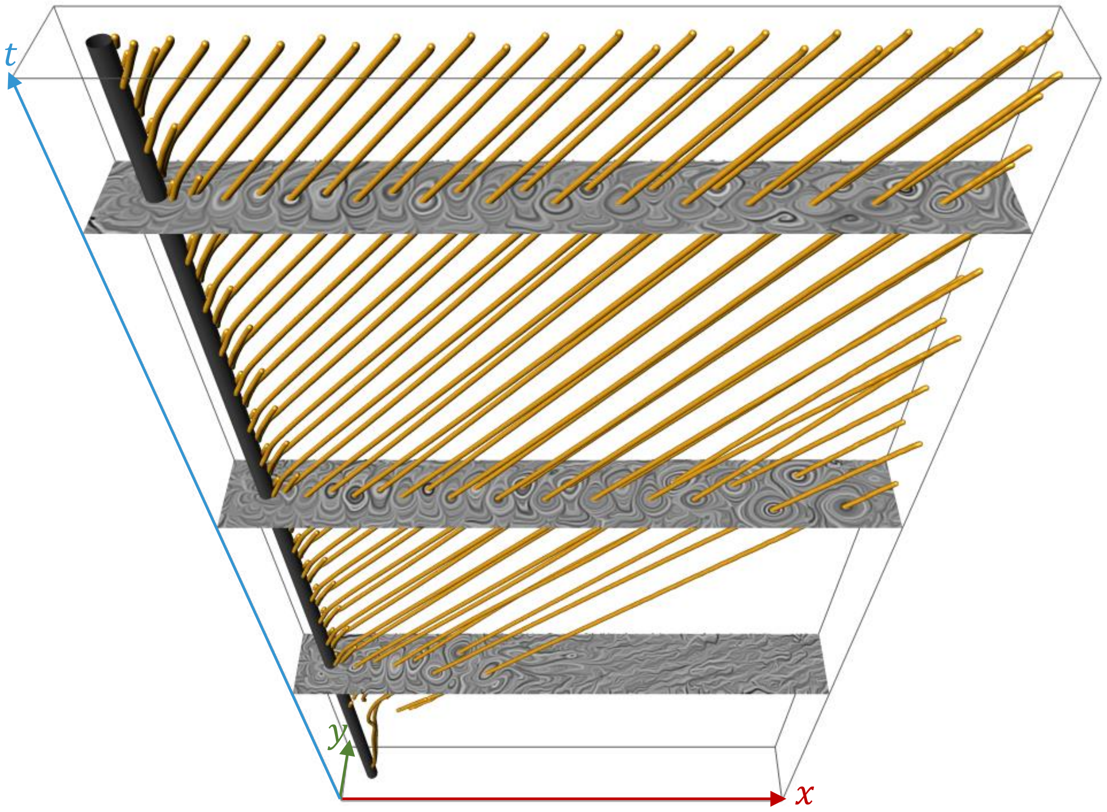
- Our network has not seen obstacles or boundary data
- Our parametric mixture model can be improved for better accuracy
- Extension to 3D



Our CNN-based approach on Noisy Data

» **Summary**

- We utilize a CNN to combine two steps of the visualization pipeline in an end-to-end manner: the filtering and the feature extraction.
- By conditioning the neural network to noisy inputs and resampling artifacts, we obtain numerically more stable results than existing optimization-based approaches.
- We formulate a parametric vector field mixture model based on Vatistas velocity profile useful for any local deep learning-based feature extraction.



Our CNN-based approach on Noisy Data

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Robust Reference Frame Extraction from Unsteady 2D Vector Fields with Convolutional Neural Networks

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