Supervised convolutional networks for volumetric data enrichment from limited sectional data with adaptive super resolution

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Introduction

Spatio-temporal fluid big data

- Exponential development of computing power
- Expensive numerical simulations (DNS, LES)
  - CFD data with an immense number of spatio-temporal discretized points [1]
- Efficient data handling methods are eagerly desired [2]

[1] Kajishima and Taira, Springer, 2017 [2] Fukami et al., JFM, 2021

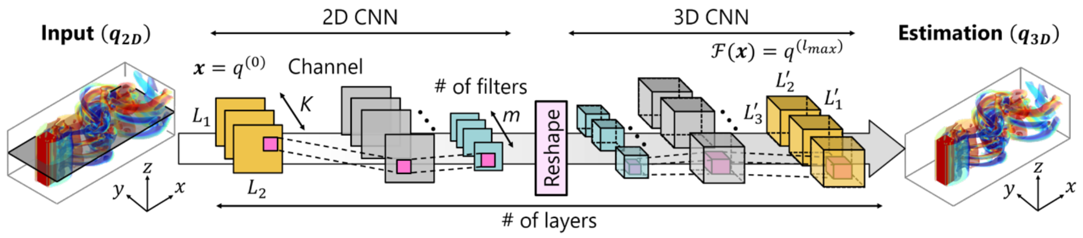
Neural-network-based state estimation

- Neural network can reconstruct flow fields from limited data
  - Estimation from sensors to a whole field [3]
  - Super-resolution analysis [2,4]
- Next challenge: 3D reconstruction from 2D sectional data towards efficient data compression
- Example: a flow around the square cylinder at Re_D=300

[3] Erichson et al., PRSA, 2020
[4] Fukami et al., JFM, 2019

Methods

2D-3D Convolutional Neural Network [5]



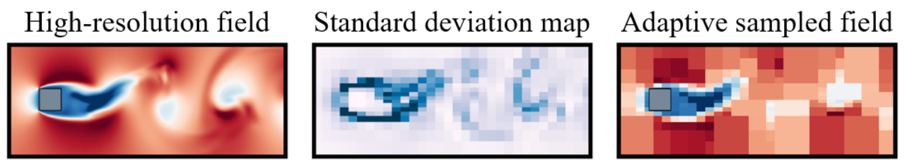
[5] LeCun et al., *Proc. IEEE*, 1998

$$\boldsymbol{w} = \mathrm{argmin}_{\boldsymbol{w}} ||\boldsymbol{q}_{3D} - \mathcal{F}(\boldsymbol{q}_{2D}; \boldsymbol{w})||_2$$

- Input: Velocity field of several x-y sectional fields ($\boldsymbol{q}_{2D}$)
- Output: Velocity field of the whole domain ($\boldsymbol{q}_{3D}$)
- Data: a flow around the square cylinder obtained by DNS

Combination with *adaptive sampling*-based super resolution

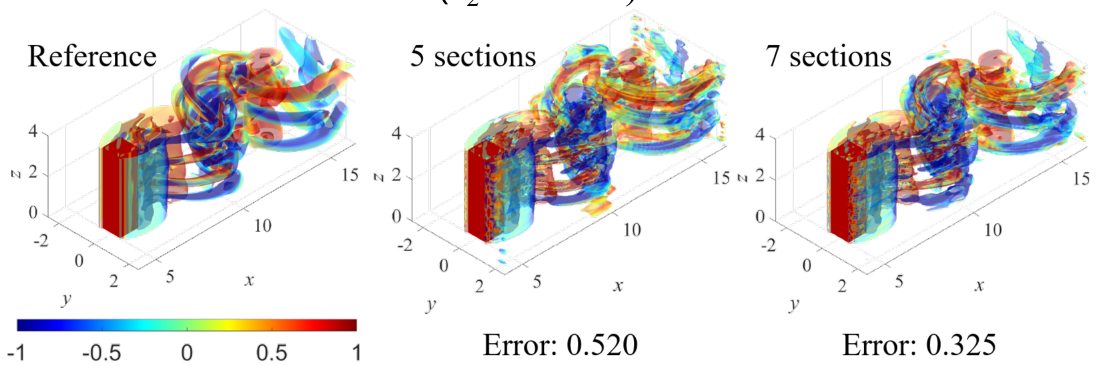
- Towards the data reconstruction while saving a storage
- *Adaptive sampling*-based low-resolution data
  - Determine the sampling ratio of the area by accounting for the 'importance'
  - Importance: the spatial standard deviation of velocity



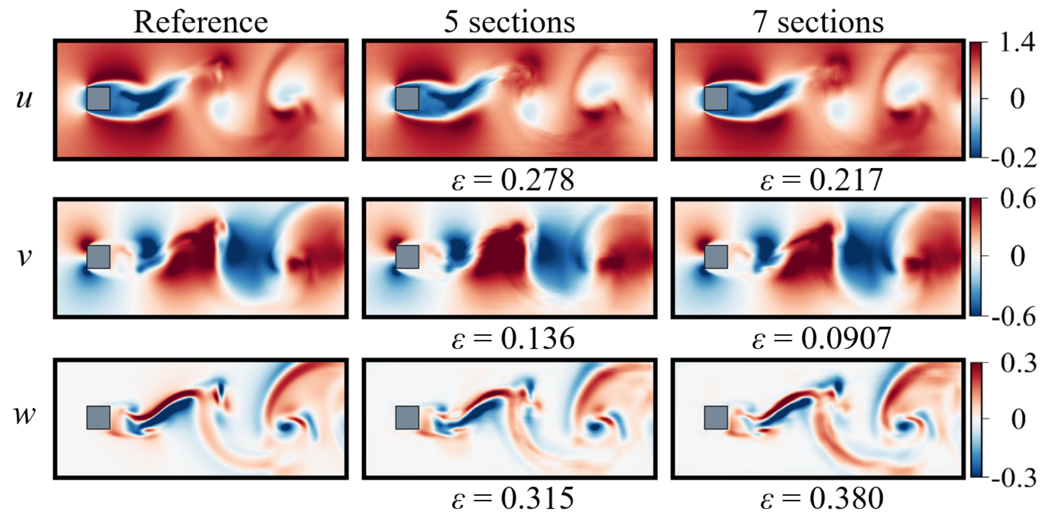
Results

1. 3D reconstruction from 2D high-resolution cross sections

- Reconstructed fields (λ_2 = -0.001)



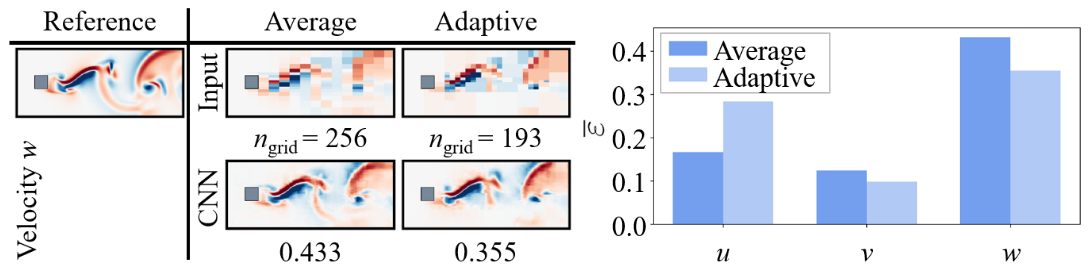
  - The use of more input sections provides a wake reconstruction with the higher accuracy
- Estimated cross-sectional velocity fields



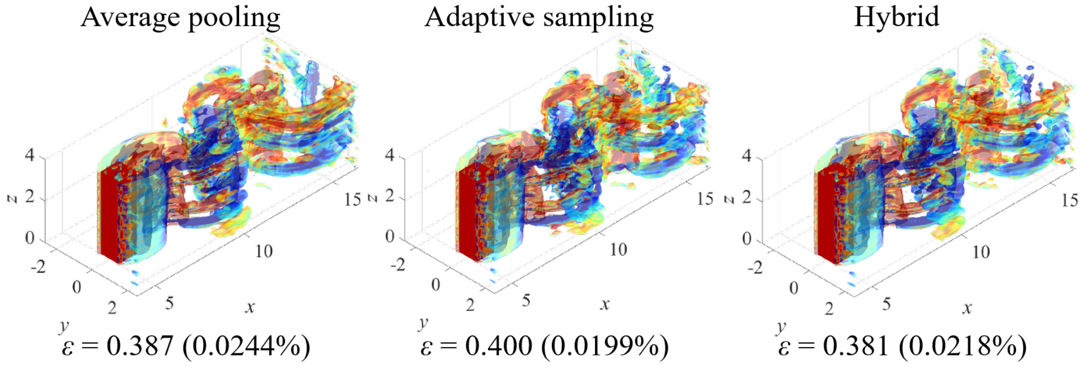
  - The reconstructed fields are in reasonable agreement with the reference DNS $\varepsilon = ||\boldsymbol{q}_{\mathrm{DNS}} - \boldsymbol{q}_{\mathrm{ML}}||_2 / ||\boldsymbol{q}'_{\mathrm{DNS}}||_2$

2. 3D reconstruction from 2D low-resolution cross sections

- Super-resolution reconstruction from adaptive-sampled low-resolution data



  - The estimation accuracy with adaptive sampling is superior to that of conventional average pooling in the v and w components
  - Efficient data compression can be achieved with appropriate pooling methods for each component
- 3D reconstruction from adaptive-sampled cross sections



  - Hybrid: Average pooling in the u component
    Adaptive sampling in the v and w components
  - Reasonable reconstruction from only 0.022% of the original utilizing the hybrid method

Conclusion

- 2D-3D CNN was constructed and applied to a flow around a square cylinder
- Reconstructed fields were in agreement with the reference
- Compressed data by 1/4600 of the original with adaptive-sampled super-resolution assisstance

Reference
M. Matsuo, T. Nakamura, M. Morimoto, K. Fukami, K. Fukagata, "Supervised convolutional network for three-dimensional fluid data reconstruction from sectional flow fields with adaptive super-resolution assistance," arXiv:2103.09020, 2021

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