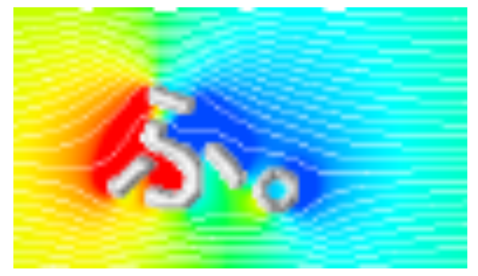
Keio University

CNN-AE/LSTM based turbulent flow forecast on low-dimensional latent space



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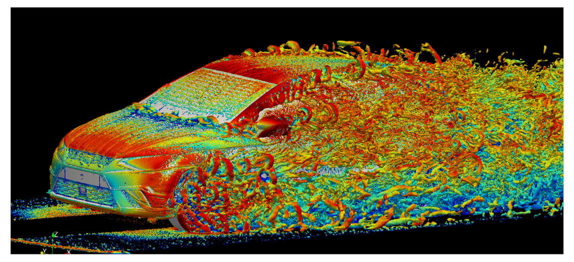
Introduction

Spatio-temporal big data of nonlinear system

- High-dimensional data with the immense number of discretization points in both space and time directions



[1]

- Development of computational storage and resources
- How to deal with this vast amount of simulation data?

[1] Barcelona Supercomputing Center, https://www.bsc.es/discover-bsc/organisation/research-departments/large-scale-computational-fluid-dynamics

Neural network based reduced order surrogate

- Good candidate to handle complex nonlinear systems
- Neural network based reduced order model for Burger's eq. [2]
  - CNN-AE & LSTM can represent the advection-dominated system while outperforming conventional linear methods
- Higher dimension problem — 2D unsteady laminar flows [3]
- Next challenge: more practical manner such as 3D turbulence
  - Example: turbulent channel flow at $Re_\tau = 110$

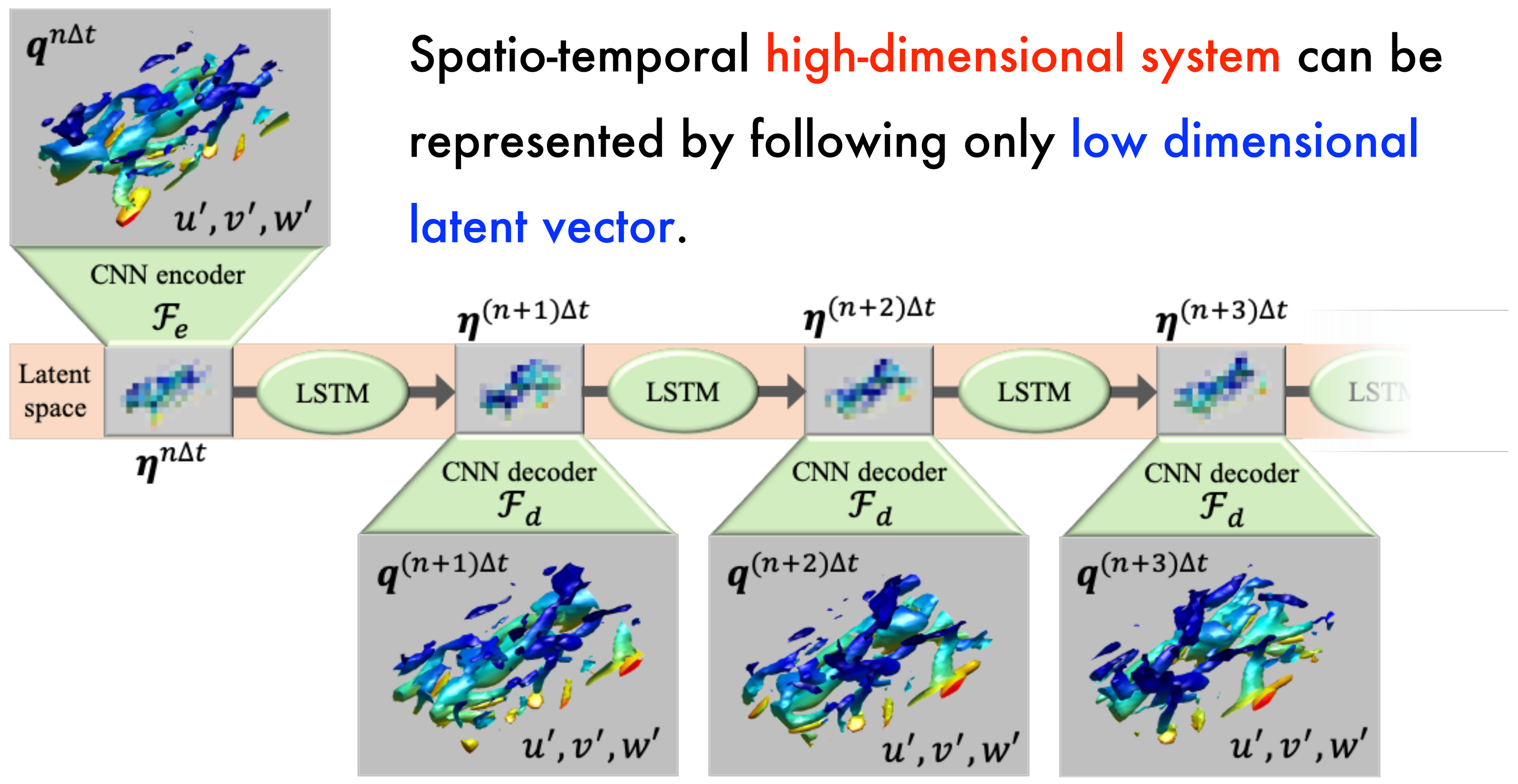
[2] Maulik et al., arXiv preprint, 2020

[3] Hasegawa et al., *Theor. Comp. Fluid Dyn.*, 2020

Methods

CNN-AE/LSTM based reduced order model

Spatio-temporal high-dimensional system can be represented by following only low dimensional latent vector.



- CNN encoder: map the flow fields into a latent space
- LSTM: predict the next time step in the latent space recursively
- CNN decoder: reconstruct the flow fields from the latent vector

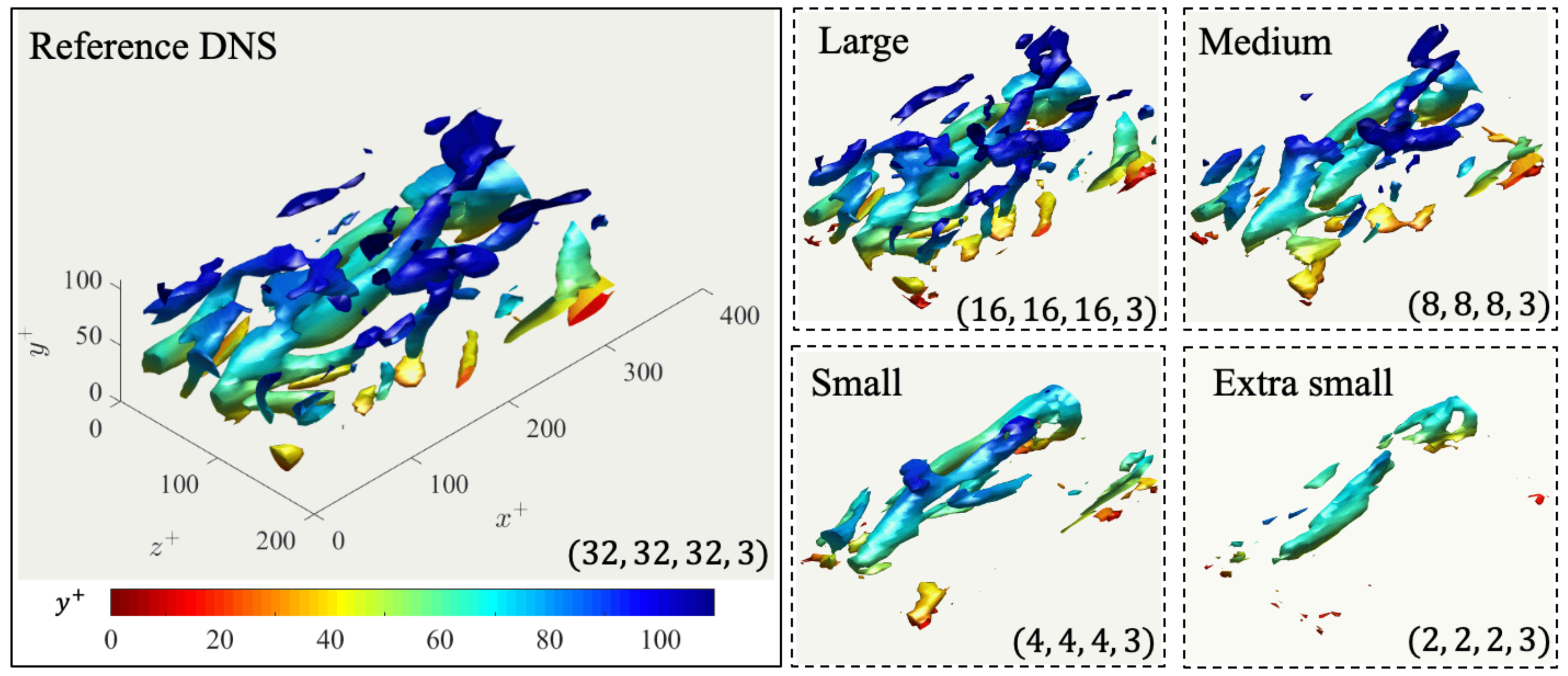
Model configuration

- Data: turbulent channel flow obtained by direct numerical simulation
- Consider several CNN-AEs whose latent vector sizes are varied
  - Large / Medium / Small / Extra small
- Train LSTM with latent vector obtained by CNN-AE
  - Medium / Small

Results

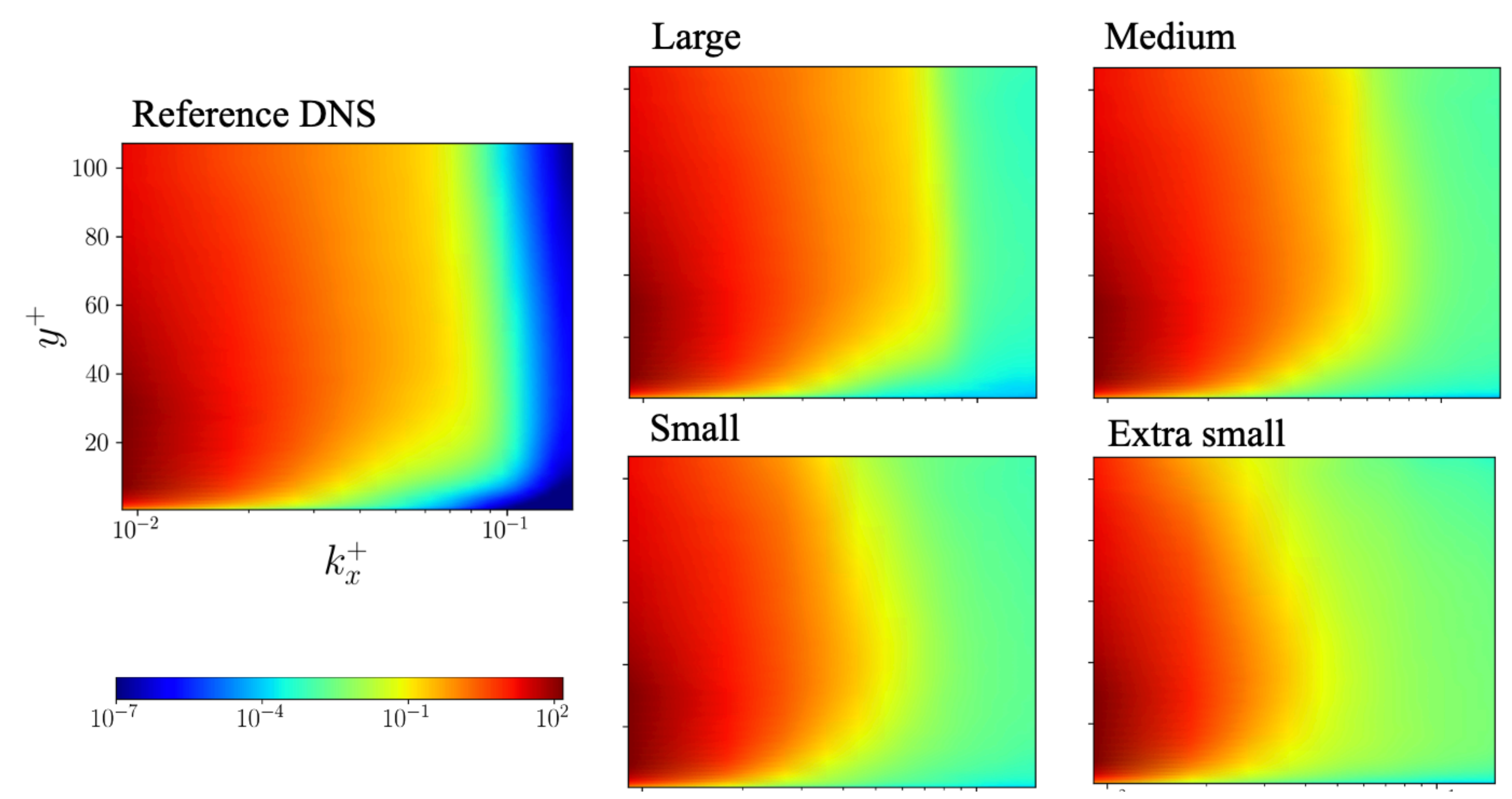
Mapping ability of CNN-AE

- Vortex structure



- \`Large' & \`Medium' model reconstruct the small structure
- \`Small' model reconstructs only large structure

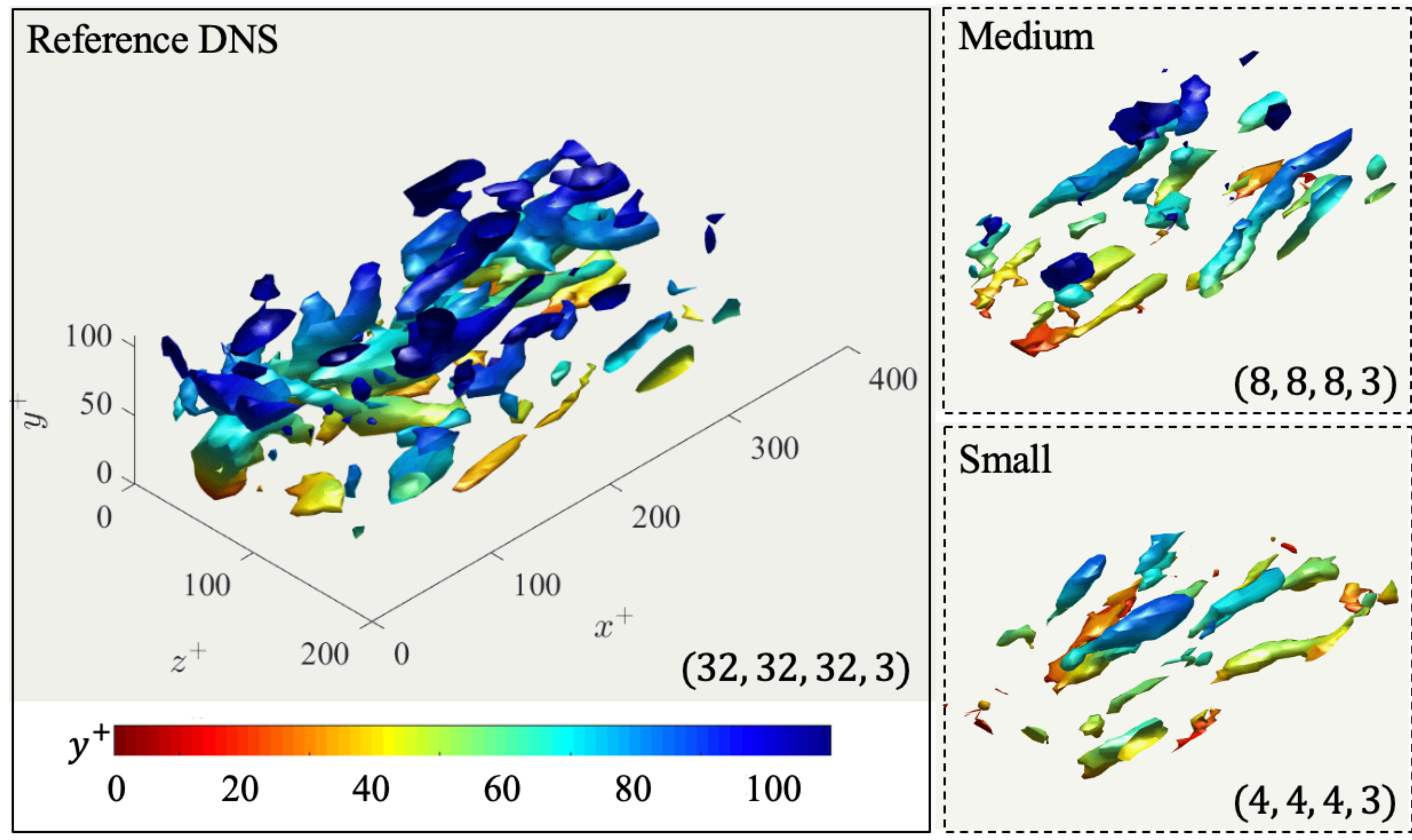
- Streamwise energy spectrum



- Lower wavenumber components are extracted preferentially
- Because of the repeated pooling operations inside CNN-AE

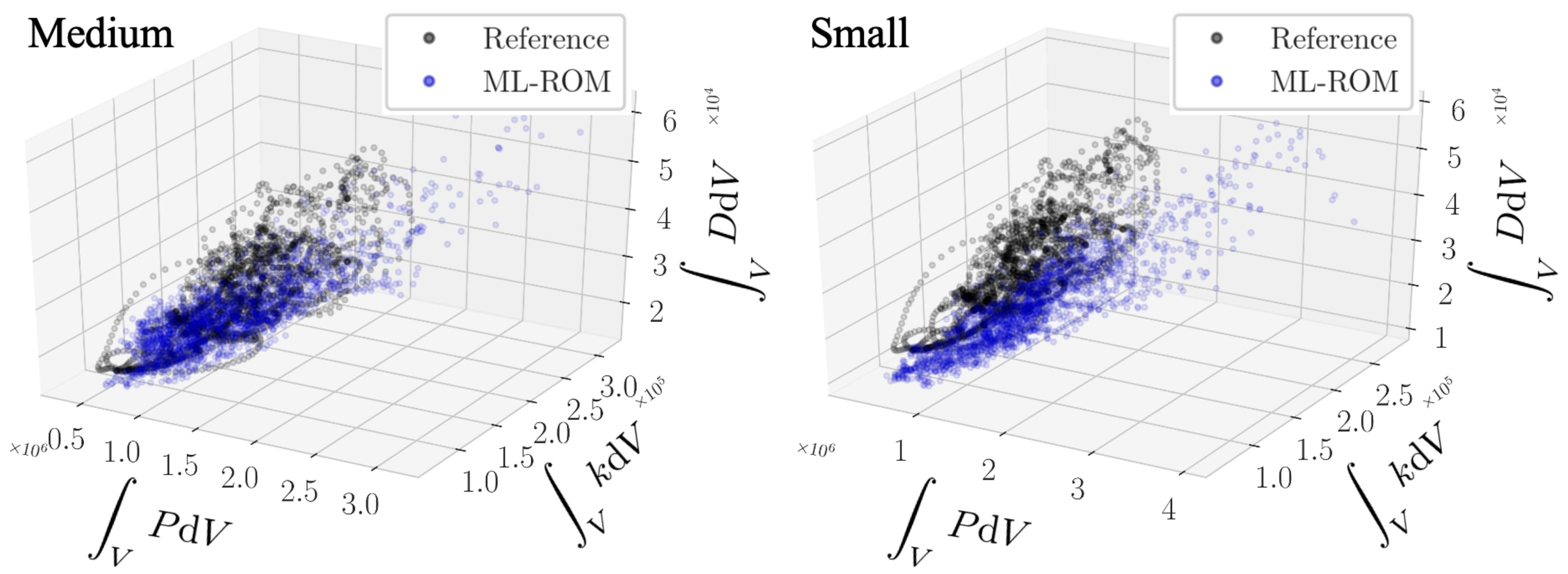
Prediction of temporal evolution via LSTM

- Vortex structure



- \`Medium' model predicts temporal evolution of flow field like DNS

- Orbital behavior in the phase space



- The trajectory of 'Medium' model overlaps that of the reference
- Attractor may exist in the similar position in the phase space

Conclusion

- CNN-AE/LSTM based reduced order surrogate was constructed and applied to a turbulent channel flow
- CNN-AE: able to map the flow field into 1.56% sized latent space
- LSTM: predict the next time step in the latent space recursively

Reference

T. Nakamura, K. Fukami, K. Hasegawa, Y. Nabae, K. Fukagata, "Extension of CNN-LSTM based reduced order surrogate for minimal turbulent channel flow," arXiv:2010.13551, 2020

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