Application of Machine Learning in Feature Identification for Complex Fluid Flow

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Backgrounds

High precision data

High- resolution spatiotemporal data

From large-scale fluid simulations and experiments

Machine learning algorithm (ML)

- K-means clustering
- PCA / POD
- Neural Networks (NN)
- SVM
- …

Nonlinear fluid dynamics
(turbulence modeling …)

Backgrounds

Success of ML in fluid mechanics community

- Data-driven turbulence modeling
- Use NN to predict life coefficients of an airfoil
- Directly predict velocity/pressure field in steady flow
- Replace Galerkin Projection with NN in reduced order modeling (ROM)
- …

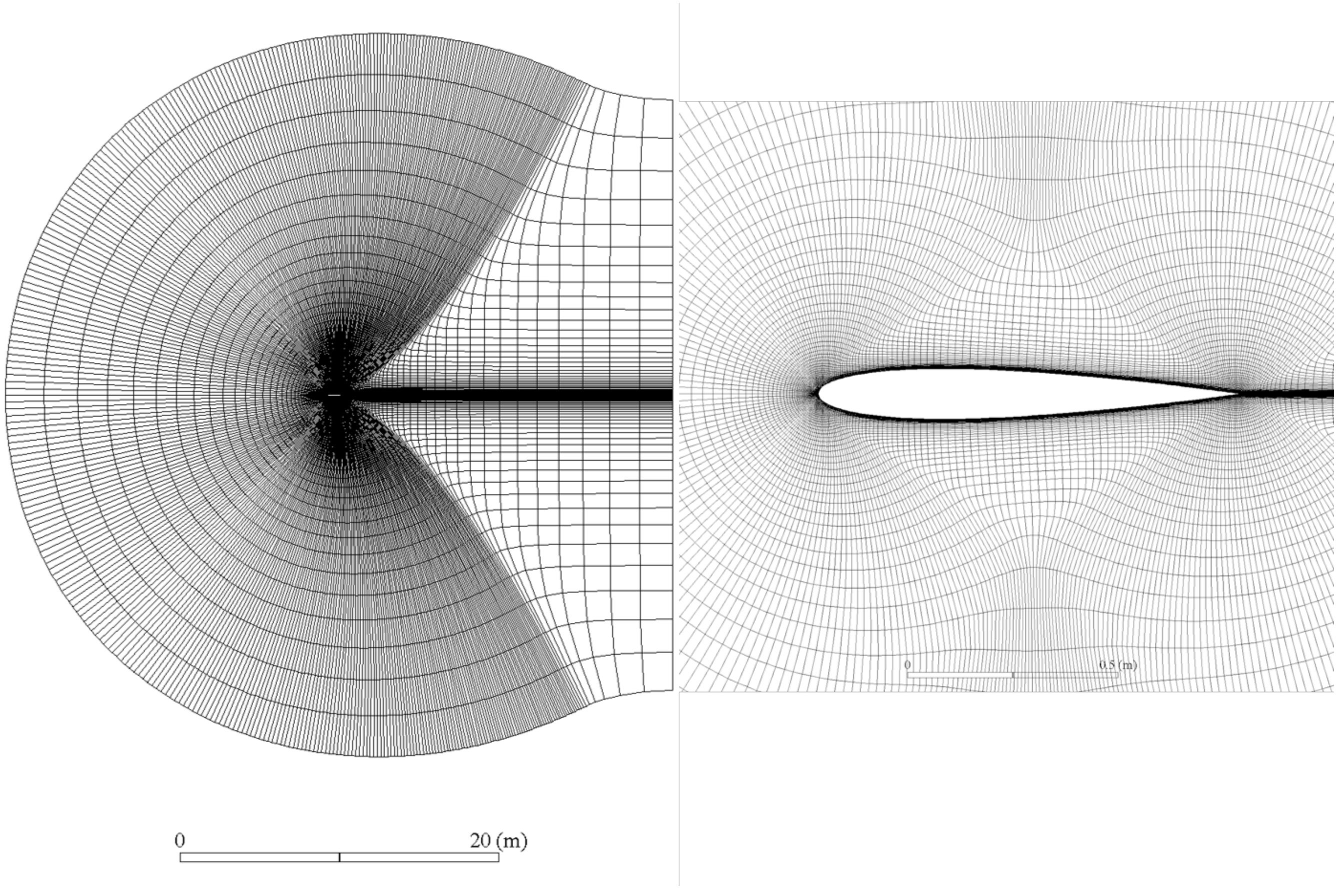
→ ML can extract some key flow features for use in establishing a nonlinear mapping relationship with the desired output

Backgrounds

The procedure of this work can be divided into three steps:

1. Train a high-accuracy convolutional neural networks (CNN) to recognize several different subsonic buffet flows over a high-incidence airfoil
2. The convolutional kernels and corresponding feature maps, identified entirely by the ML algorithms, are extracted to analyze
3. Sensitivity analysis to hyperparameters including network architectures and convolutional kernel size was explored.

Method



Full view (left) and close-up view (right) of the 2D airfoil grid used for UDNS simulations

Symmetric NACA 0012 airfoil

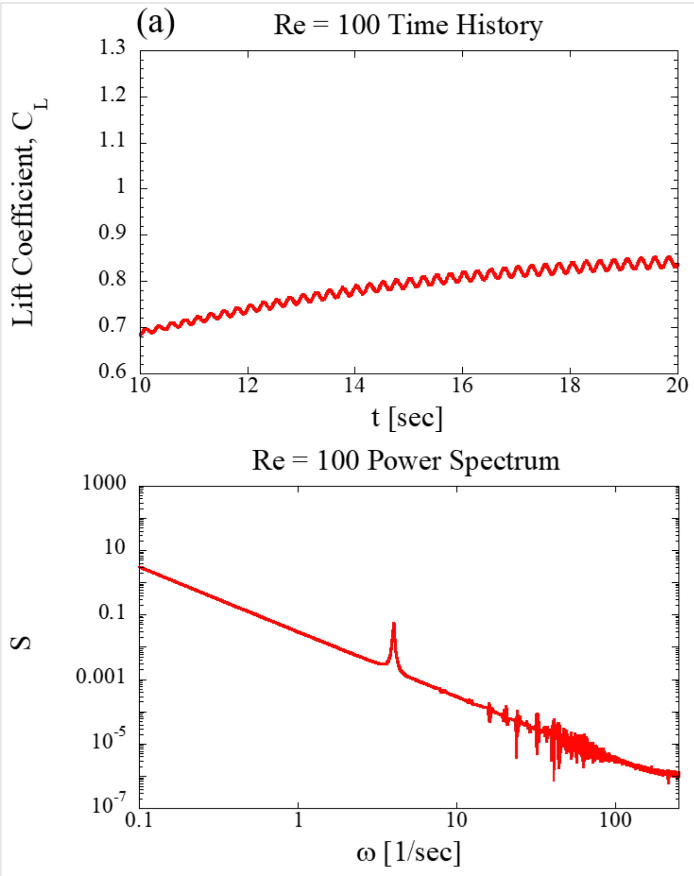
- Incidence angle : 40 degrees
- Mach number : 0.05
- Constant time step : 0.002 s
- Reynolds numbers :

100 / 600 / 1k / 10k / 100k / 1M

All six simulations started with a control volume at rest and converged to a statistically steady state

Method

Re = 100 ··· Re = 1M



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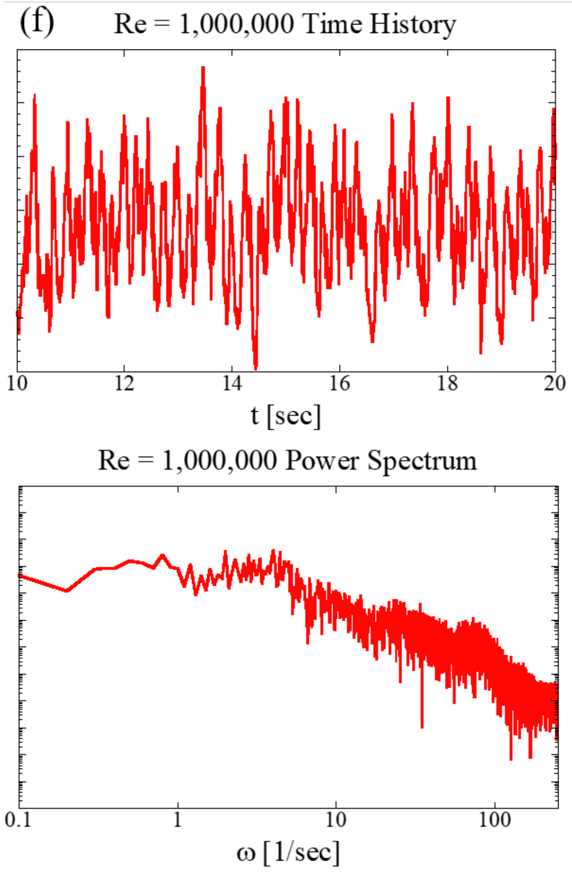


Different Re elicited a spectrum of temporal fluctuating flows over the airfoil
— subsonic buffet

Heuristic flow characterization:

(each Re is associated with qualitatively different flow regimes)

Reynolds Number	Sampling region $(t_s - t_f)/\Delta t$	Flow regime
100	8000 – 10,000	Periodic flow
600	8000 – 10,000	Quasi-periodic flow
1,000	8000 – 10,000	Quasi-periodic flow
10,000	5000 – 10,000	Chaotic flow
100,000	5000 – 10,000	Chaotic flow
1,000,000	5000 – 10,000	Chaotic flow

Flow of different Re are discreted into a sequence of 2D snapshots, which constructed our dataset

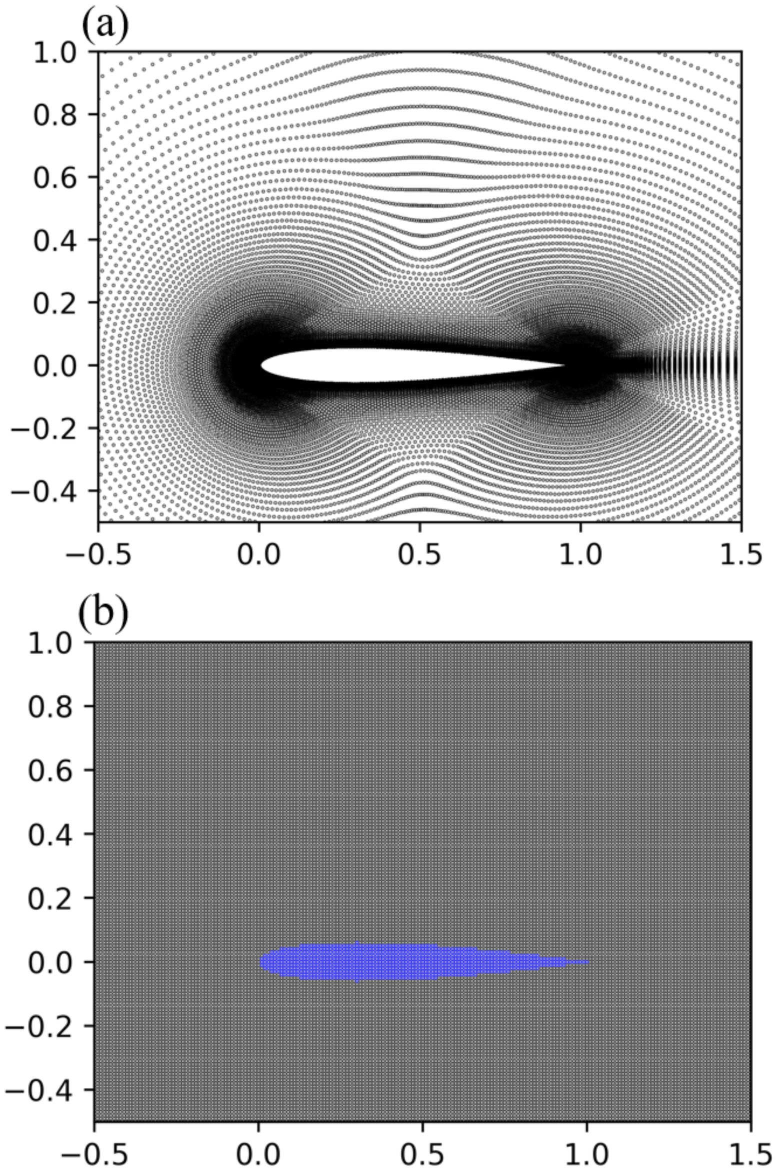
Method

Machine Learning method:

convolutional neural networks (CNNs)

- Good at processing multidimensional inputs
- CNNs are particularly successful when the input data can be decomposed into some form of hierarchical basis representation; and this is often labeled as automatic feature extraction

Data preprocessing:

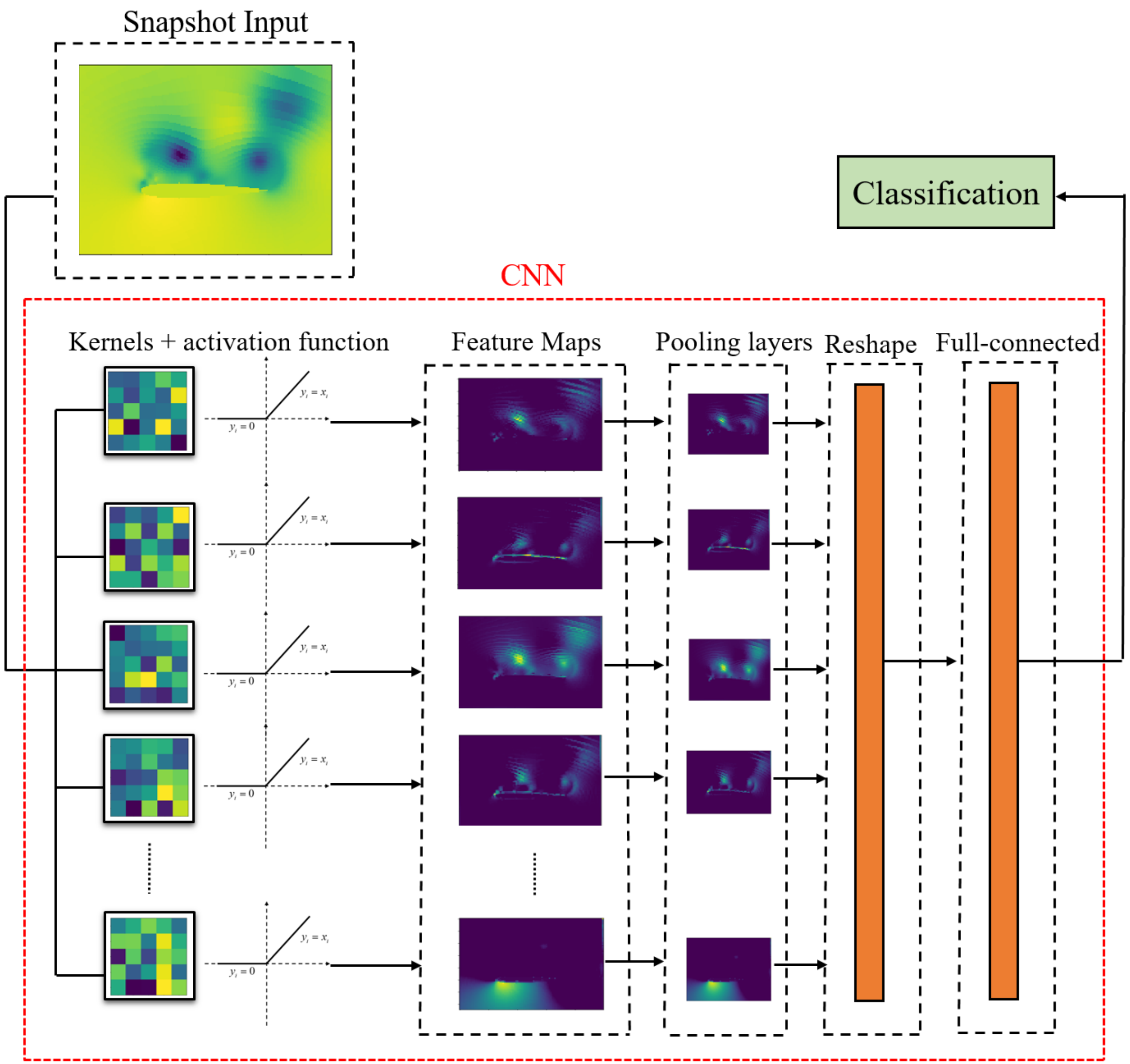


Confine the flow region for ML consideration

Cartesian grid

200 x 150

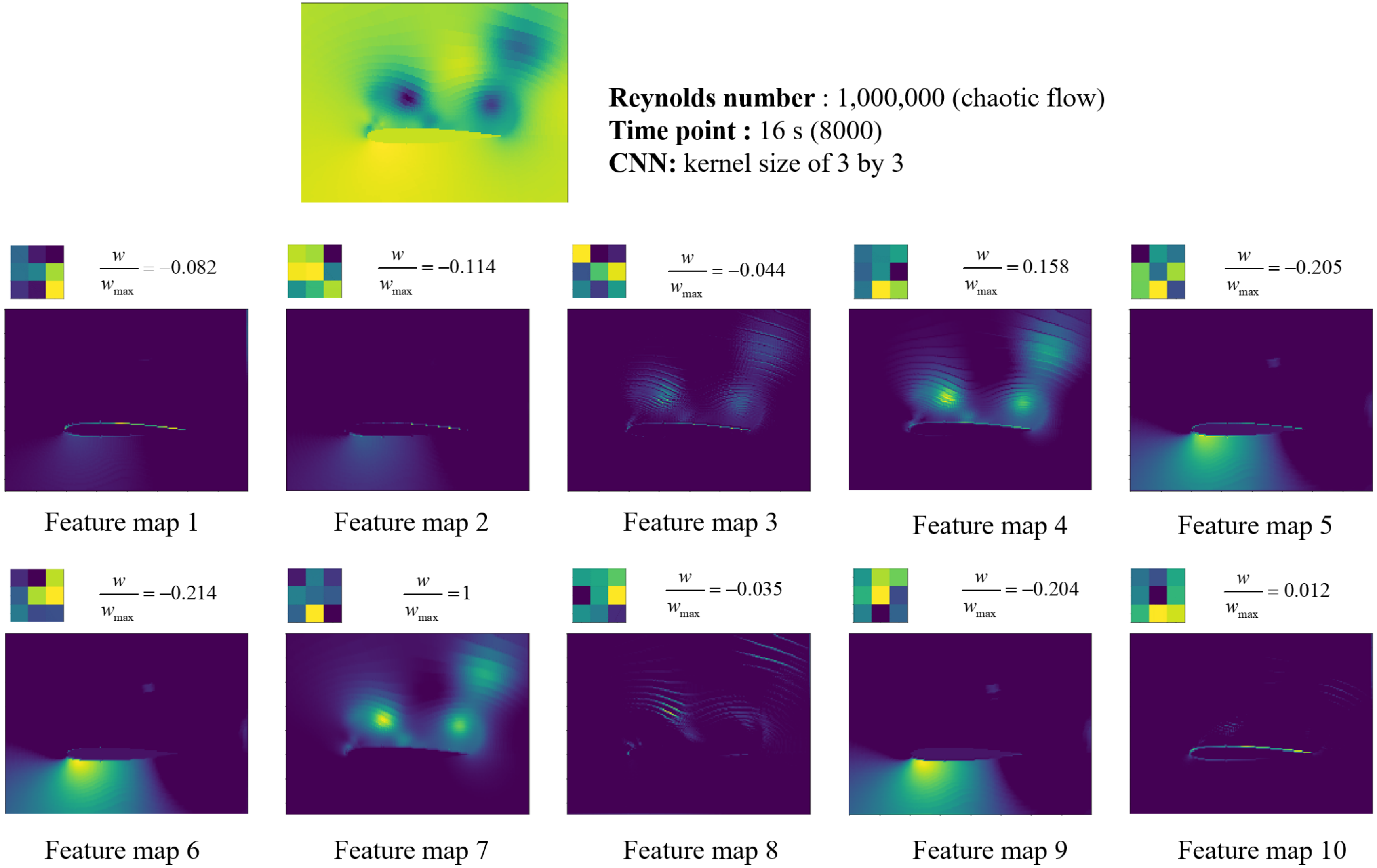
Method



The network can be divided into two steps:

- **convolutional layer** : exploit the low-dimensional, high-level representation features of the input data
- **fully- connected layer** : build the mapping relationship between these high-level representations and predictive variables

Results



Conclusions:

Edge kernels:
Feature maps 1, 10

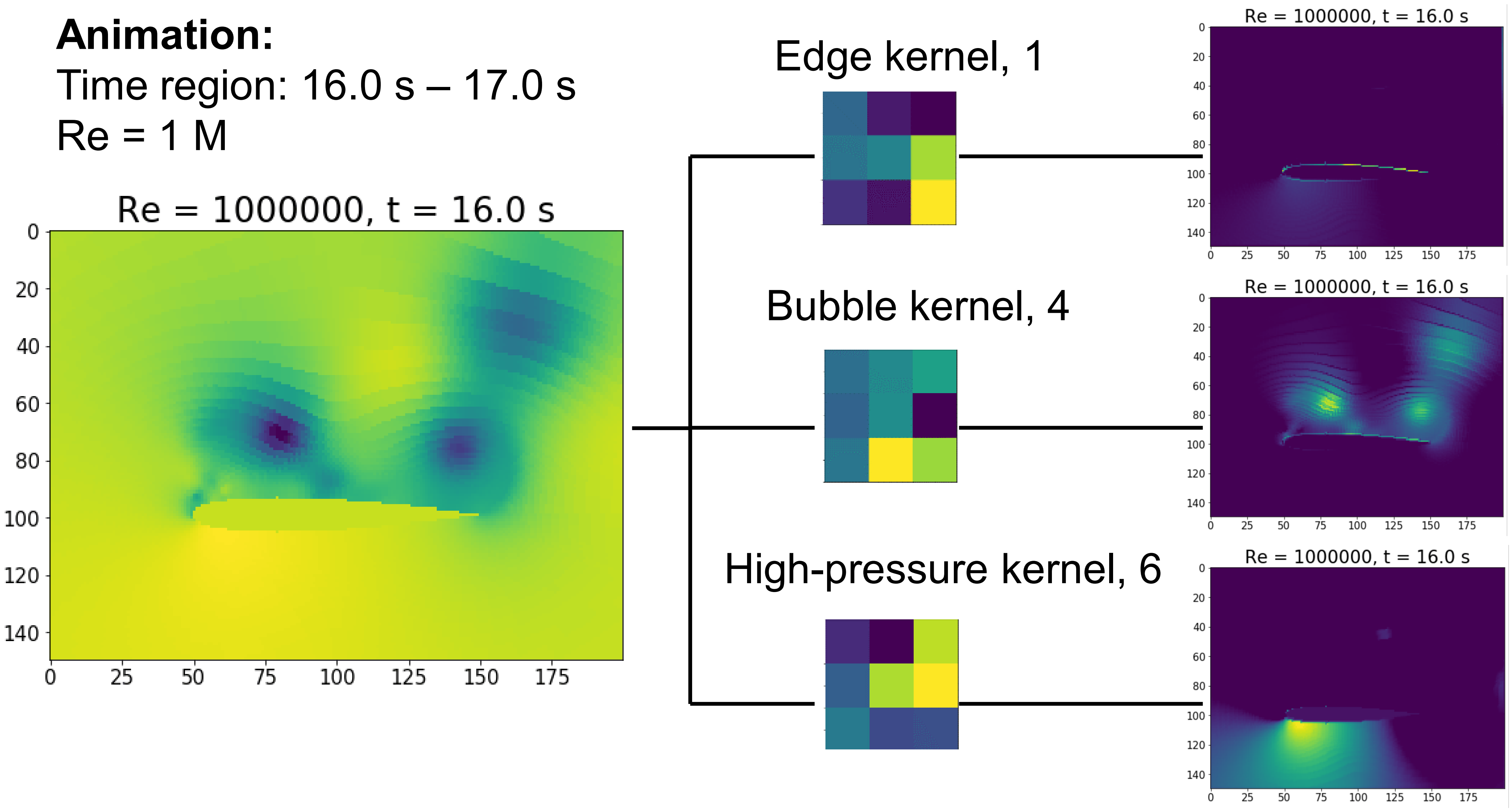
Bubble kernels:
Feature maps 4, 7

High pressure kernels:
Feature maps 5, 6, 9

Useless kernels:
Feature maps 2, 3, 8

Results

Animation:
Time region: 16.0 s – 17.0 s
Re = 1 M



Results

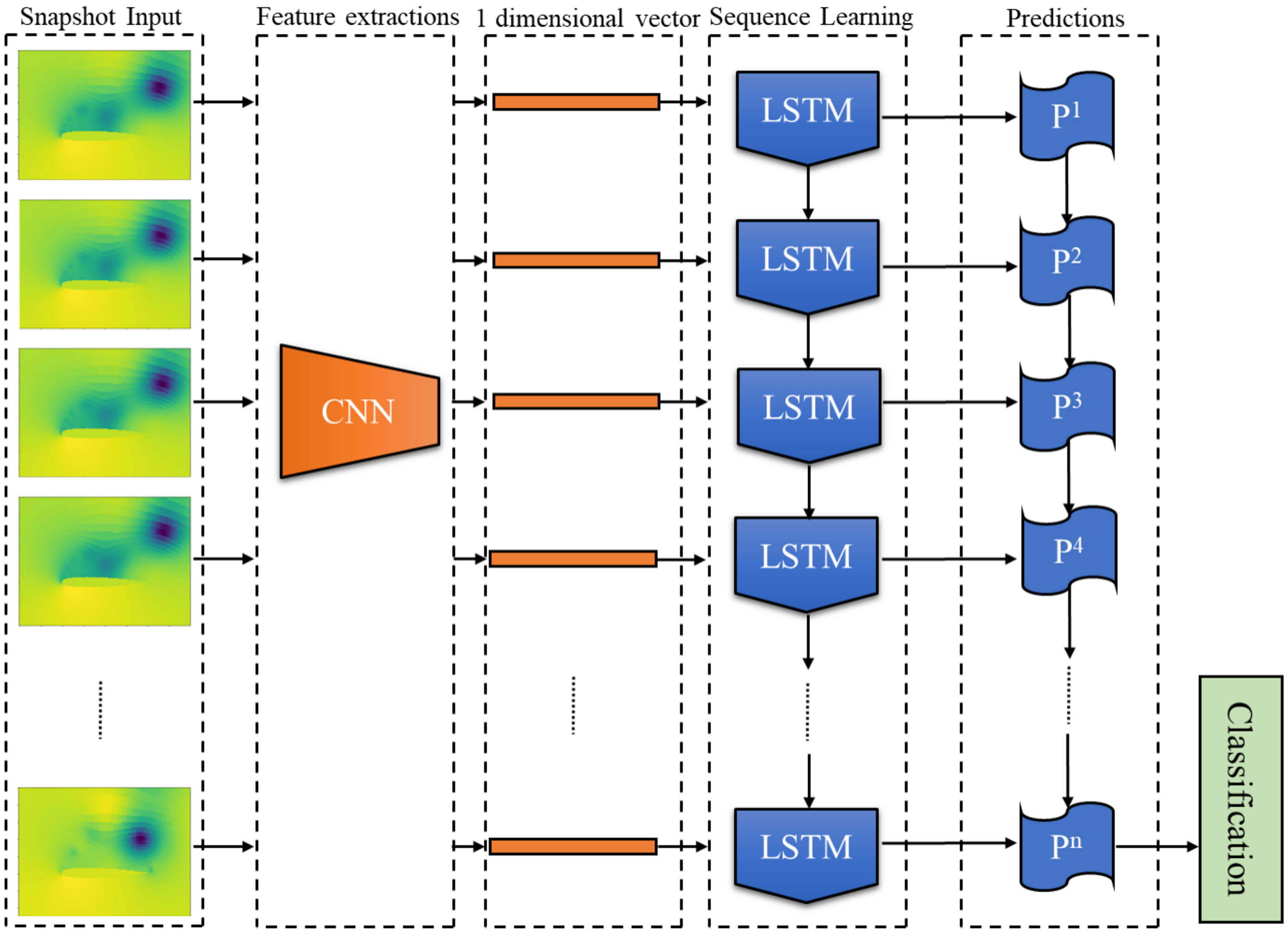
Table 1 Number of functional kernels for different trained CNNs.

Kernel size	Edge kernel	Bubble kernel	High-pressure kernel	Useless kernel
3 × 3	2	2	3	2
5 × 5	0	1	2	7
10 × 10	0	0	2	8
20 × 20	0	0	0	10

- Edge detection is known to require smaller kernels
- The pressure bubbles are themselves rarely larger than 20 pixels in diameter with this interpolated resolution —— it makes sense that in a low convolutional layer that kernels would struggle to take a form which can consistently identify the bubbles.
- Large-kernel models without identifying coherent structures still performed well in their classification task —— it can be understood by the concept of receptive field (the region of input space that affects a particular unit of the network)

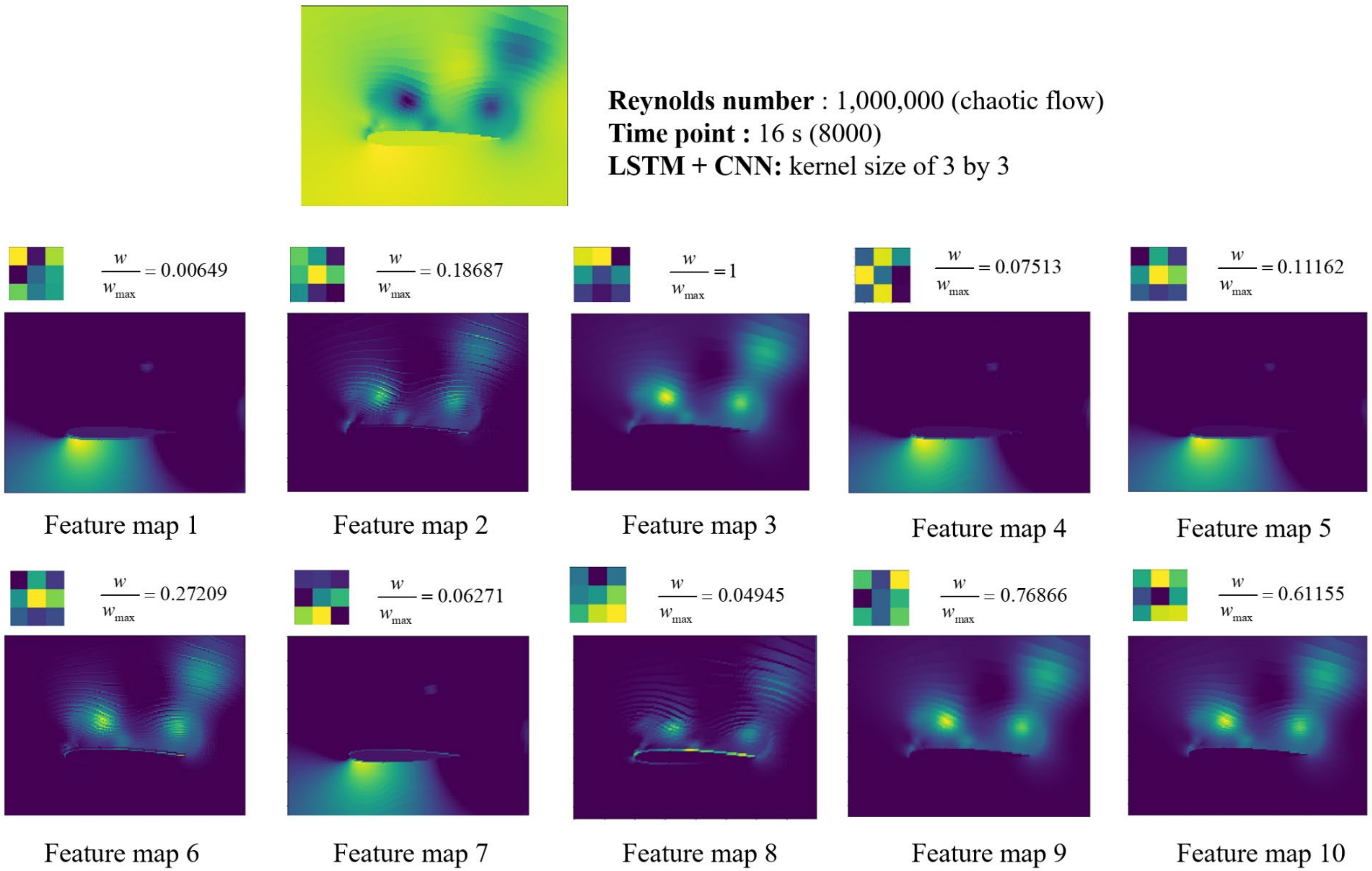
Results

CNN-LSTM neural network



- The number of snapshots in one data sequence was set to **200**.
- **Training dataset**: 30 data sequences
- **Test dataset**: 105 data sequences
- **Accuracy**: classified falsely 2 out of 105 (>98%)

Results



Results:

- The number of dynamically significant kernels increased
- The edge and useless kernels, which had low ratios of weight in the CNN, disappeared entirely

Conclusions:

- ◆ CNN-LSTM model employed only kernels which captured dynamically significant characteristics
- ◆ CNN-LSTM involves solving within a much larger parameter space and therefore requires significantly more computational resources to train

Conclusions

1. The trained CNN automatically identified three large-scale structures, including the airfoil edge, localized shedding pressure abnormalities (bubbles) and the high-pressure region near the airfoil's leading edge. This was accomplished without human intervention or knowledge of the flow's kinematics.
2. The presence of localized fluctuations in pressure, in both the bubbles and the high-pressure region, was found to inform most significantly the model's flow classification. These were the only highly weighted characteristics in the CNN model and the only ones developed in the CNN-LSTM model.
3. Smaller convolutional kernels were necessary to identify coherent structures as understandable by human users. Larger convolutional kernels still resulted in highly accurate flow classifications, but were less physically informative to the users due to the "receptive field" concept.
4. Consideration of temporal information in the CNN-LSTM improved both classification accuracy and the dynamical insight available from the trained model. The multiscale nature of the chaotic flow was identified as dynamically important by the model, again with no provided kinematic information.

Shizheng Wen, Michael W. Lee, Kai M. Kruger Bastos, Earl H. Dowell, "Application of Convolutional Neural Network in Feature Identification for Complex Fluid Flows", in submission

Outline

Thank you for listening!

Acknowledgement

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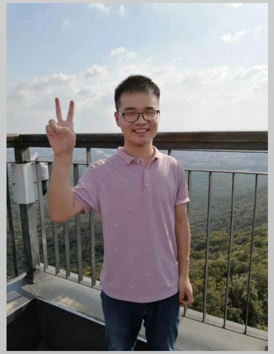

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