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Predicting High-Resolution Turbulence Details in Space and Time

KAI BAI[1], CHUNHAO WANG[1],

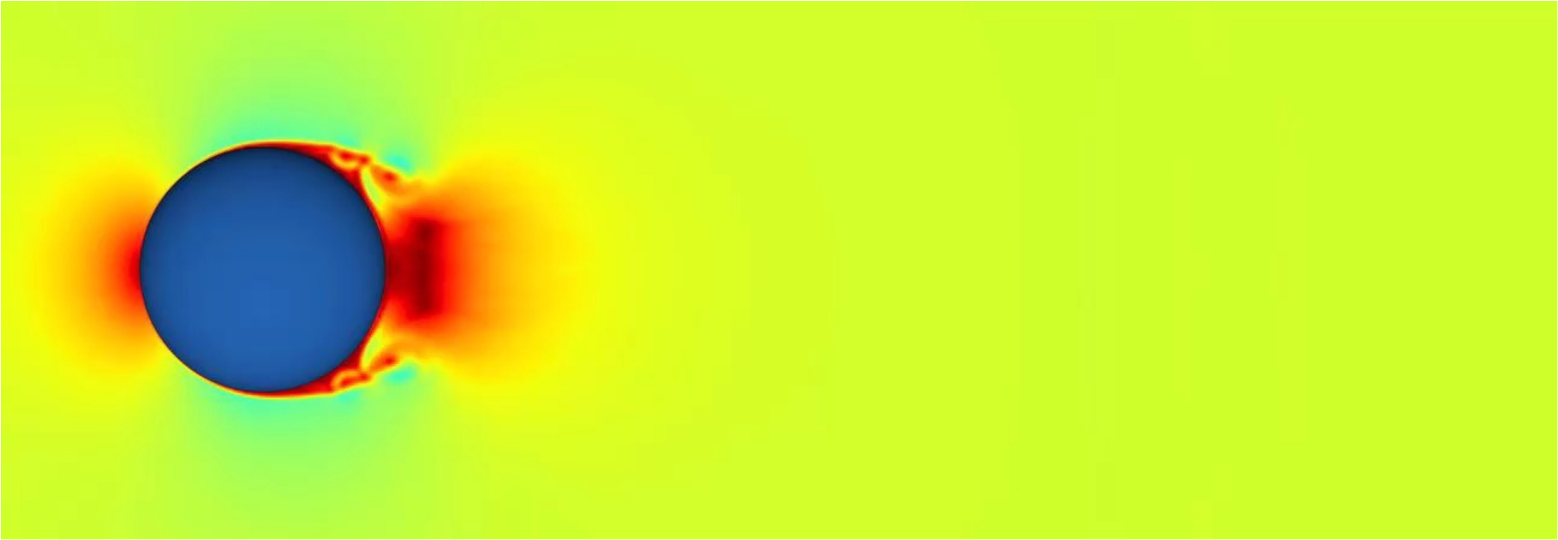
MATHIEU DESBRUN[2], XIAOPEI LIU[1]

1.SHANGHAITECH UNIVERSITY

2. INRIA / ÉCOLE POLYTECHNIQUE / CALTECH

GOAL

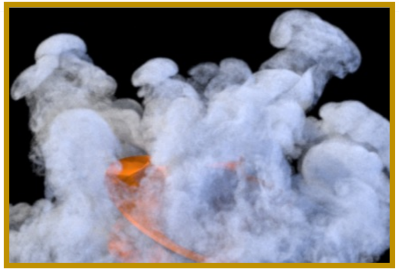
- Predicting high-resolution turbulence details in space and time



RELATED WORK


Voticity confinement
[Fedkiw et al. SIG ’01]


Modified turbulence model
[Pfaff et al. SIG ’10]


Frequency guiding
[Forootaninia et al. SIG Asia ’20]


Stream guiding
[Sato et al. SIG ’21]


[Chu et al. SIG ’17]


[Xie et al. SIG ’18]


[Um et al. SCA ’18]

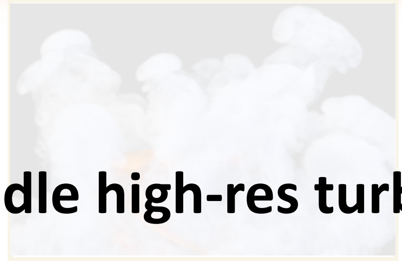

[Bai et al. TOG ’20]

RELATED WORK

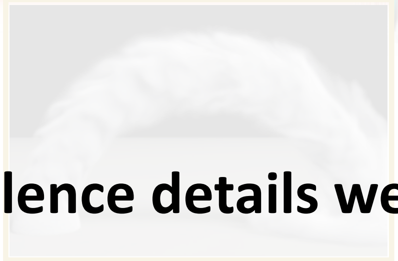
- **Previous methods cannot handle high-res turbulence details well**
- **[Bai et al. 2020] scales well, but has limited generalizability**
- **We significantly improve on their generalizability**

Voticity confinement
[Fedkiw et al. SIG '01]

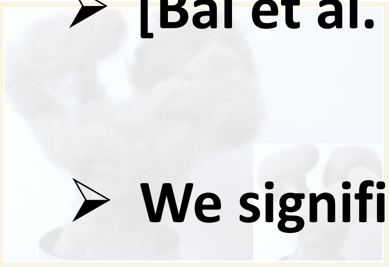
Modified turbulence model
[Pfaff et al. SIG '10]



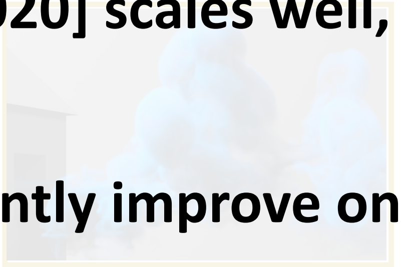
Frequency guiding
[Forootaninia et al. SIG Asia '20]



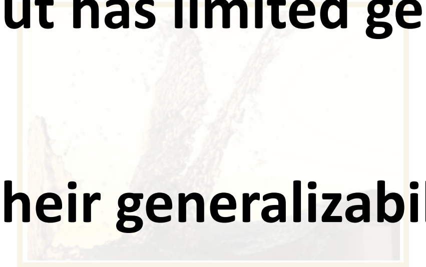
Stream guiding
[Sato et al. SIG '21]



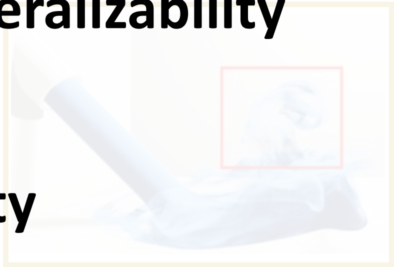
[Chu et al. SIG '17]



[Xie et al. SIG '18]



[Um et al. SCA '18]

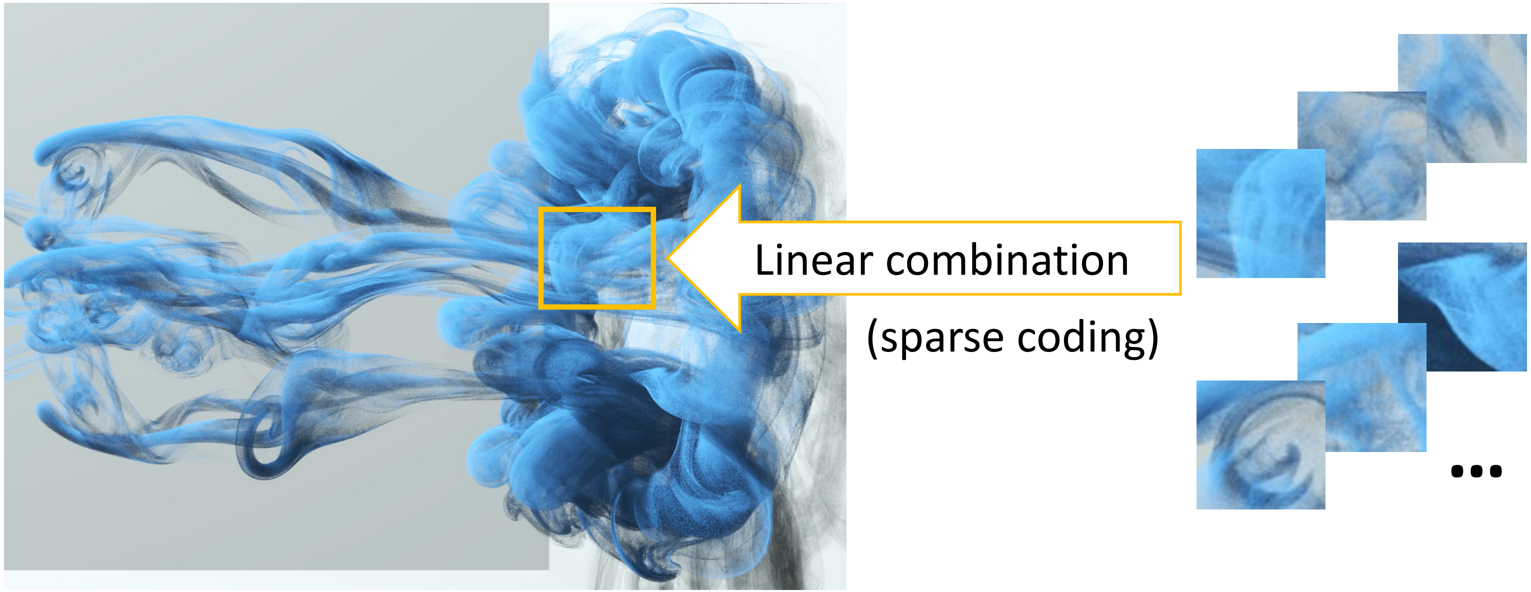


[Bai et al. TOG '20]

Recap of the approach by Bai et al. [2020]

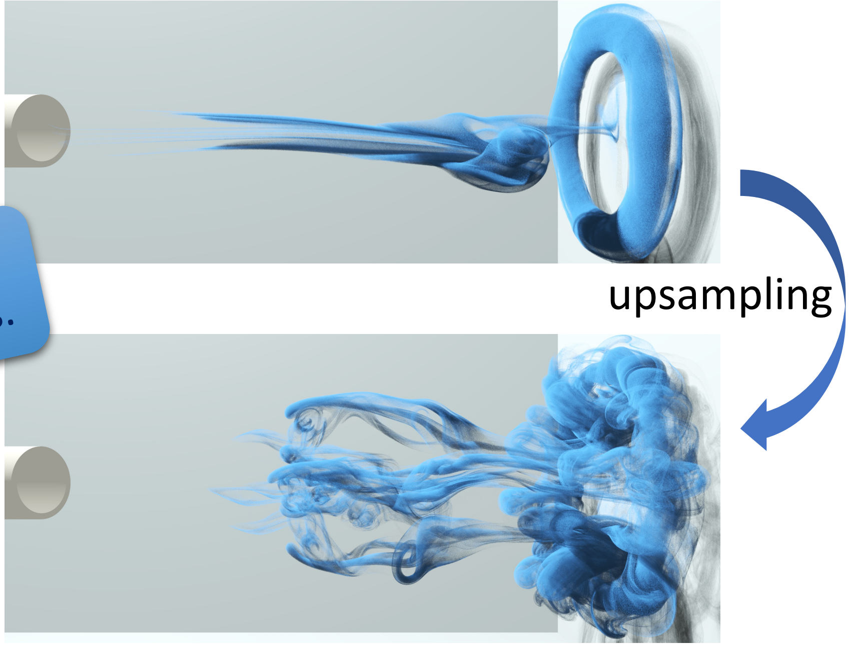
RECAP OF ORIGINAL APPROACH

Dictionary-based learning for flow synthesis [Bai et al. 2020]



RECAP OF ORIGINAL APPROACH

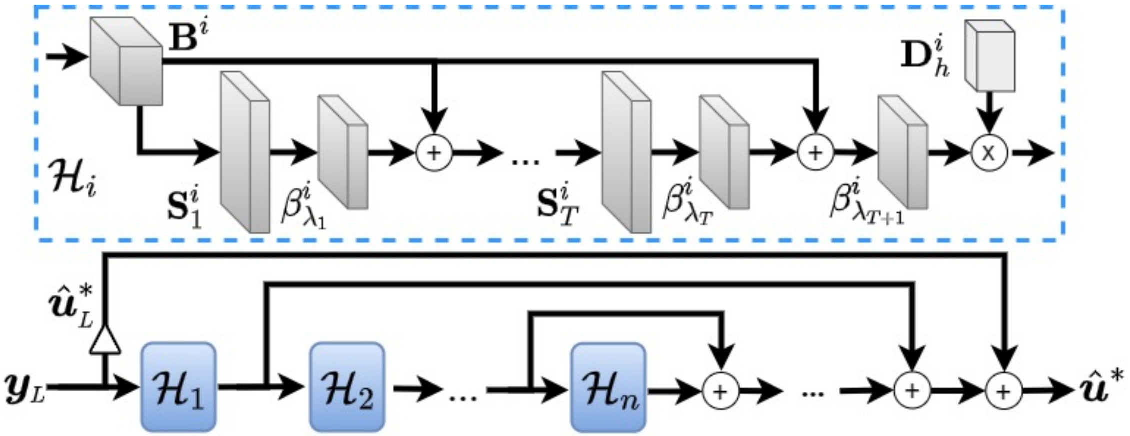
Bai et al. [2020] construct a patch dictionary for upsampling



A patch-based learning approach for predicting high-frequency flow structures.

RECAP OF ORIGINAL APPROACH

Neural network structure of Bai et al. [2020]



Multi-scale dictionary-based neural network

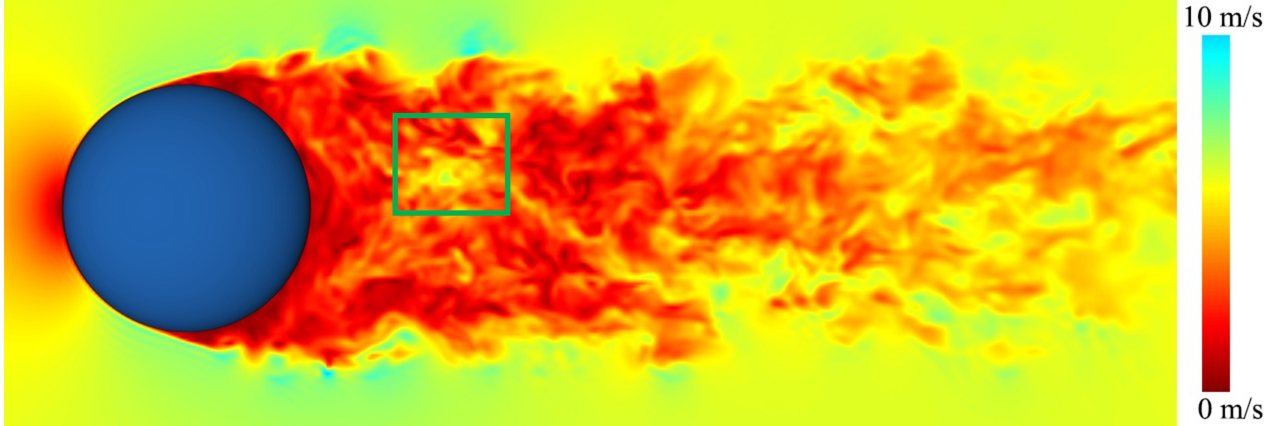
RECAP OF ORIGINAL APPROACH

Different variants proposed in [Bai et al. 2020]

- Input using up to three consecutive velocity field at times [t, t-1, t-2]
- Even include vorticity patches in the input
- Two types of patch encoding (space-time/phase-space)

Observation
&
Motivation

Characteristics of turbulent flows



Complex global structure can be synthesized as
a *combination of local structures*.

OBSERVATION

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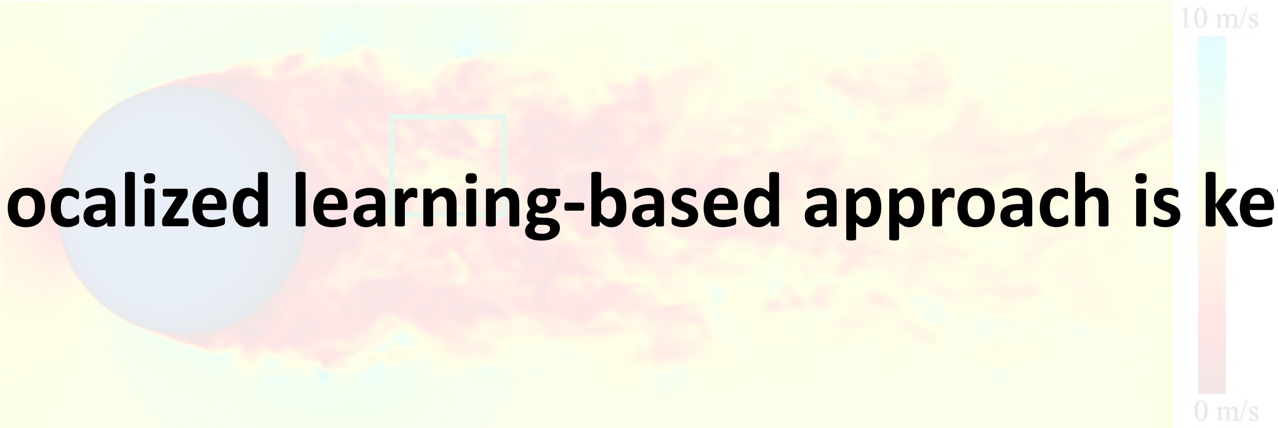
Characteristics of turbulent flows

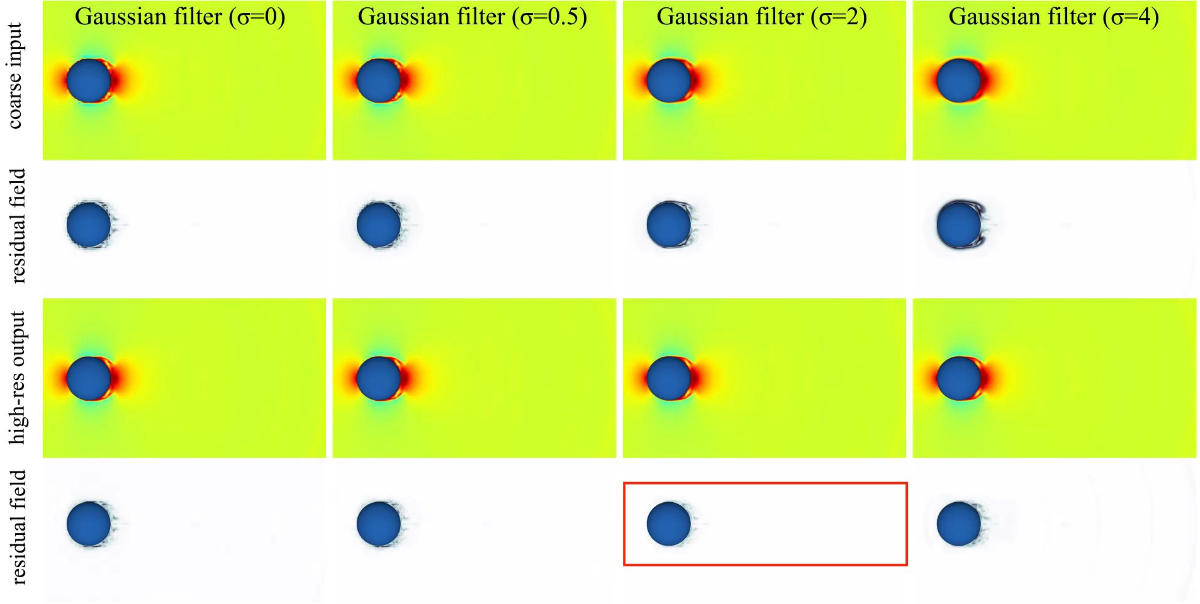


A localized learning-based approach is key!

Complex global structure can be synthesized as
a *combination of local structures.*

OBSERVATION

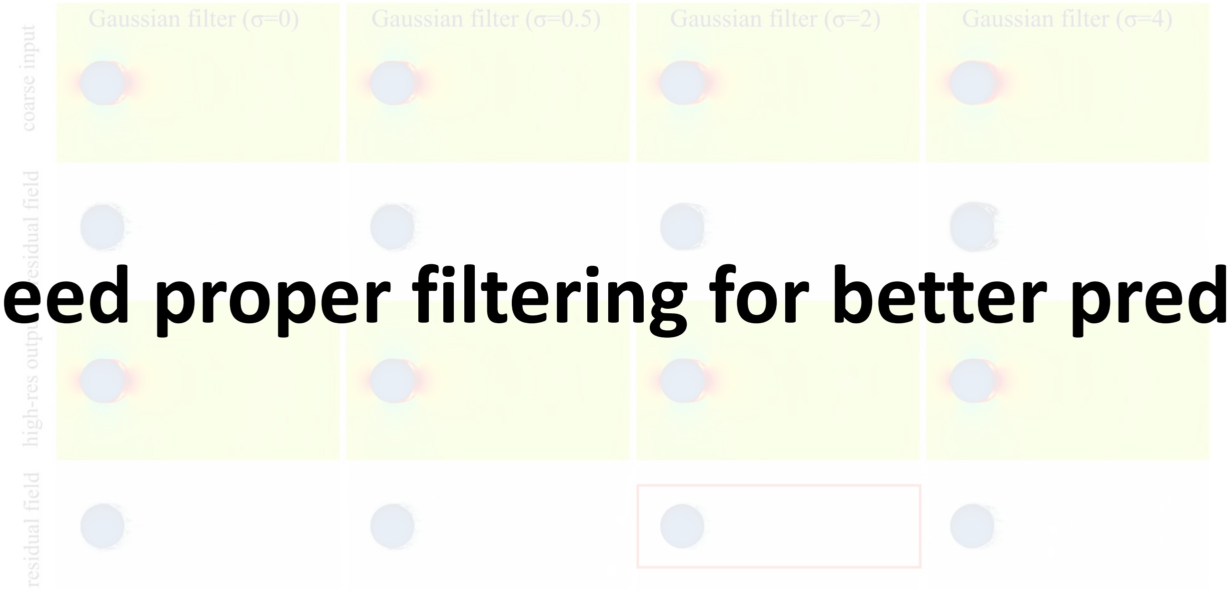
Experiments on different filtered inputs with [Bai et al. 2020]



Note that the minimal error is reached for a specific filtering (red box).

OBSERVATION

Experiments on different input filtering with [Bai et al. 2020]



We need proper filtering for better prediction!

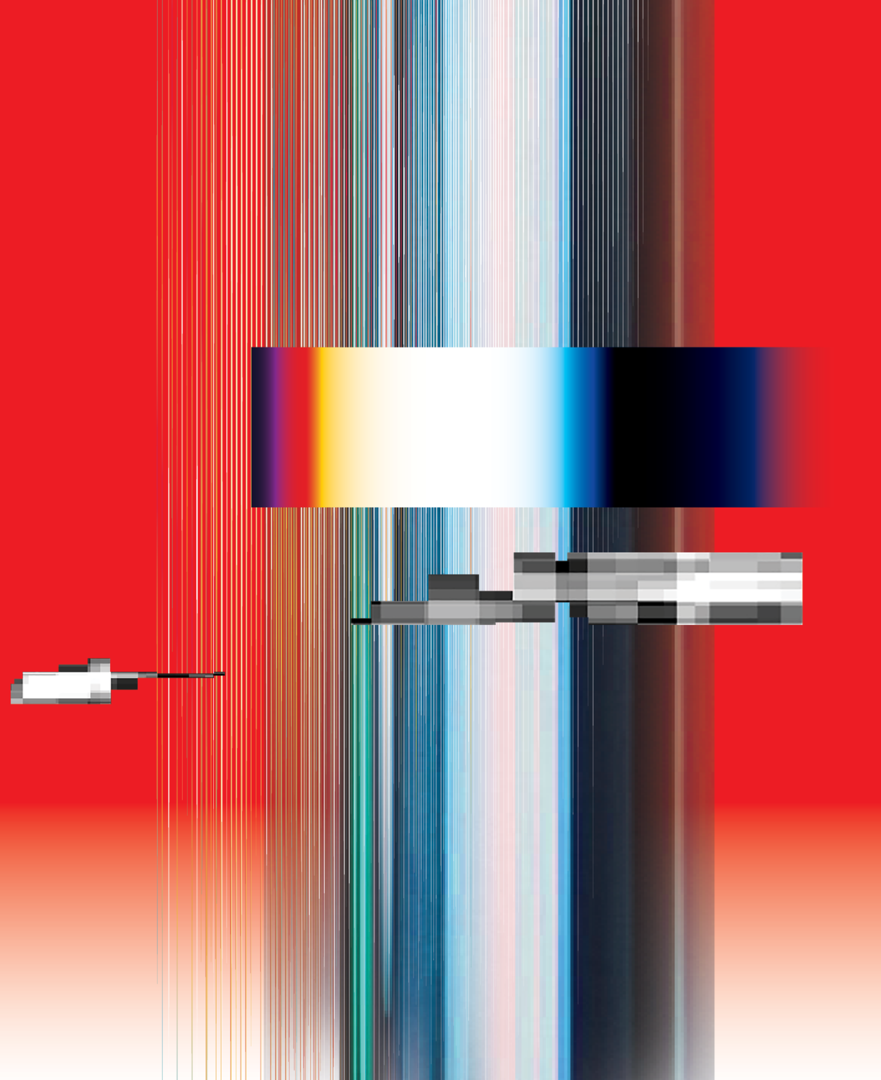
Note that the minimal error is reached for a specific filtering (red box).

MOTIVATIONS

What we realized:

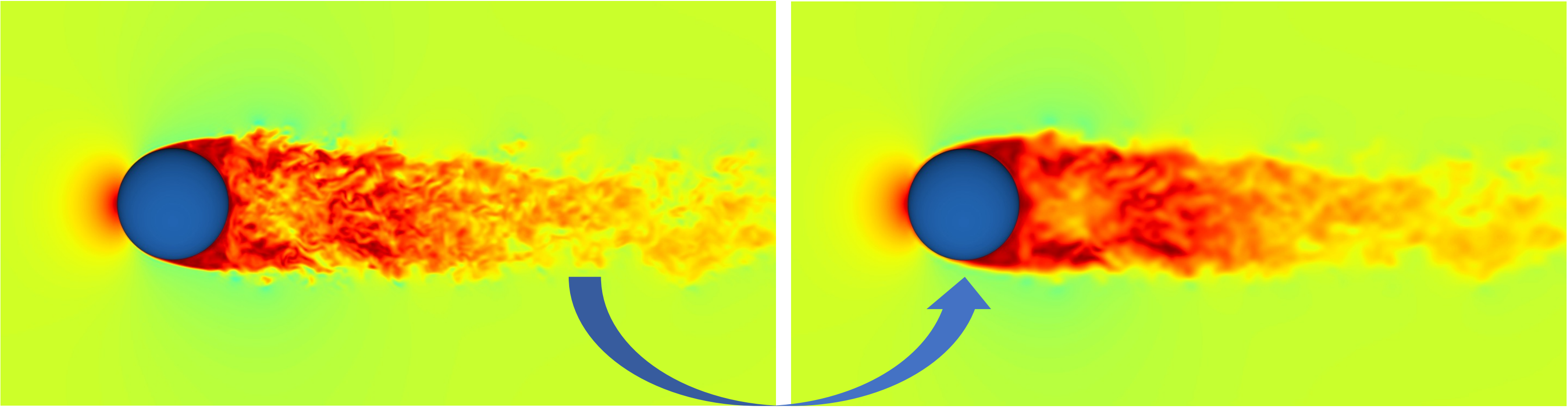
1. Aliasing artifacts in the input render the learning of detailed predictions *more difficult than it should*
2. Training patches without spurious structures makes the training much easier/faster and more generalizable
3. Incorporating a more customized filtering in the neural network is needed

New learning framework to flow upsampling



OUR NEW LEARNING FRAMEWORK

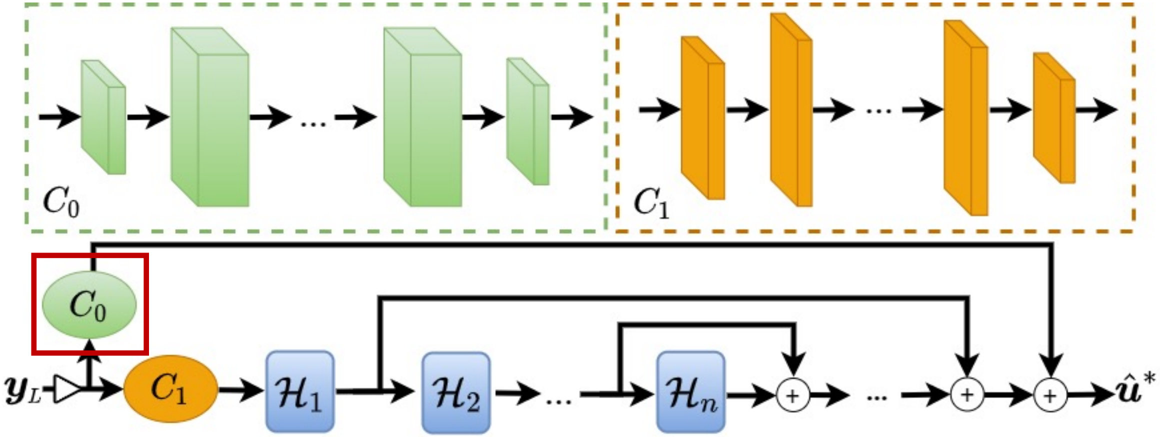
Simple low-pass filtering



Gaussian filter + downsampling

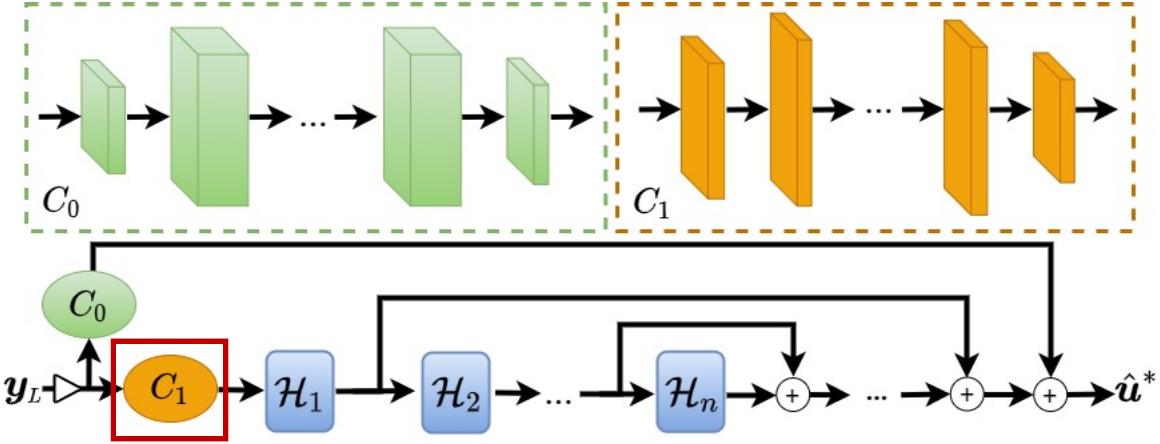
OUR NEW LEARNING FRAMEWORK

Adaptive filtering



Filter the coarse input, which is then taken as the new base flow

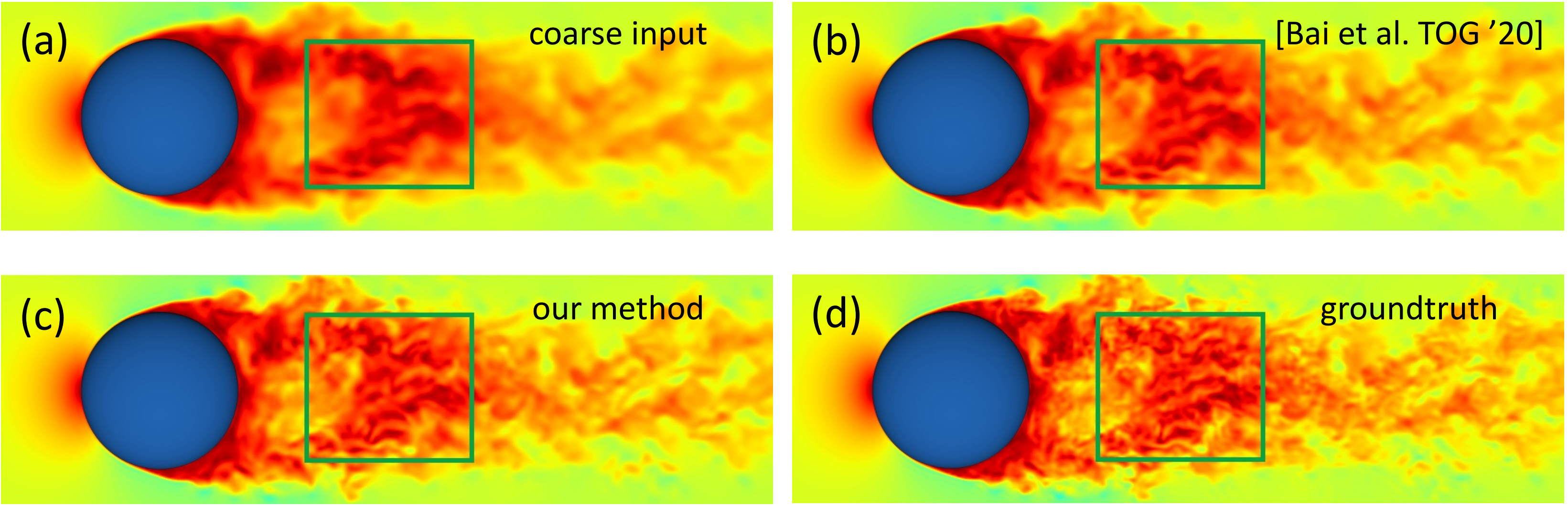
Adaptive filtering



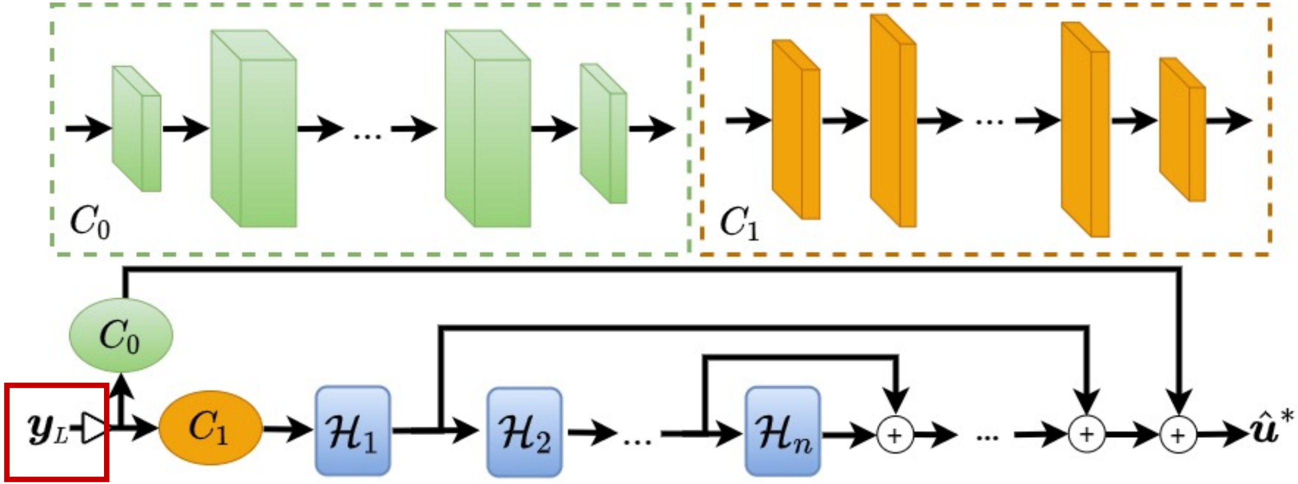
Make the coarse input more “identifiable”

OUR NEW LEARNING FRAMEWORK

Result of adaptive filtering (purely spatial upsampling)



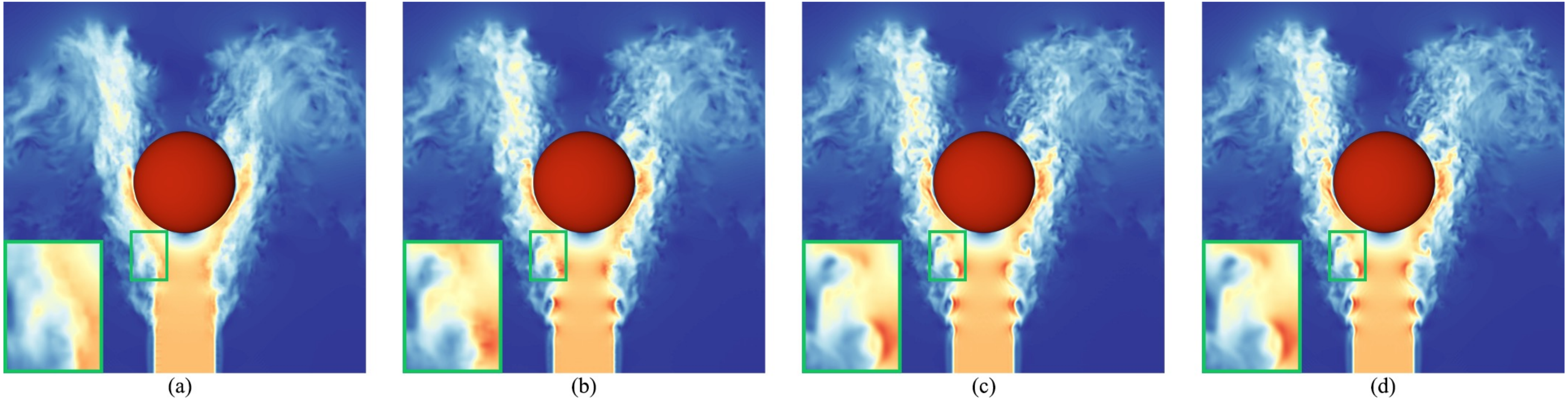
Input structure design



$y_L = [\hat{u}_L^t, \hat{u}_L^{t-1}, \gamma]$ (input vector $\gamma \in [0,1]$)

OUR NEW LEARNING FRAMEWORK

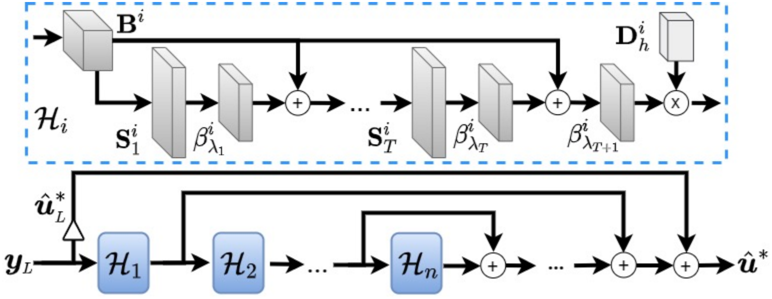
Result of input design (purely temporal upsampling)



[Bai et al. TOG ’20] | [Bai et al. TOG ’20] with our new input design | our method | groundtruth

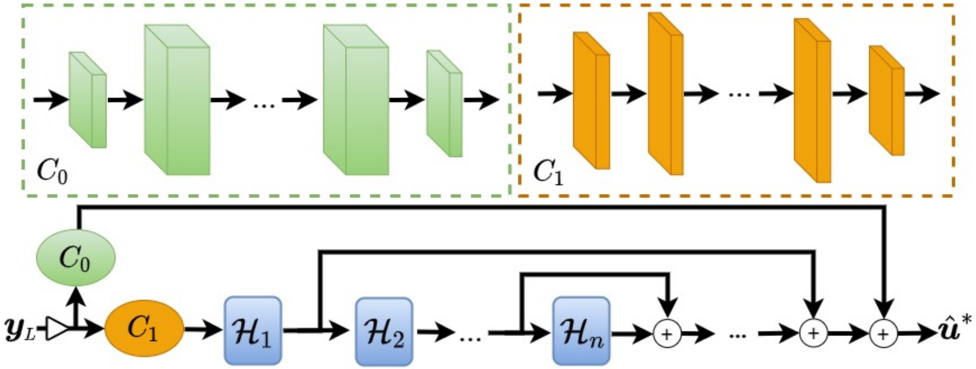
OUR NEW LEARNING FRAMEWORK

Comparison of [Bai et al. ’20] vs. our neural network

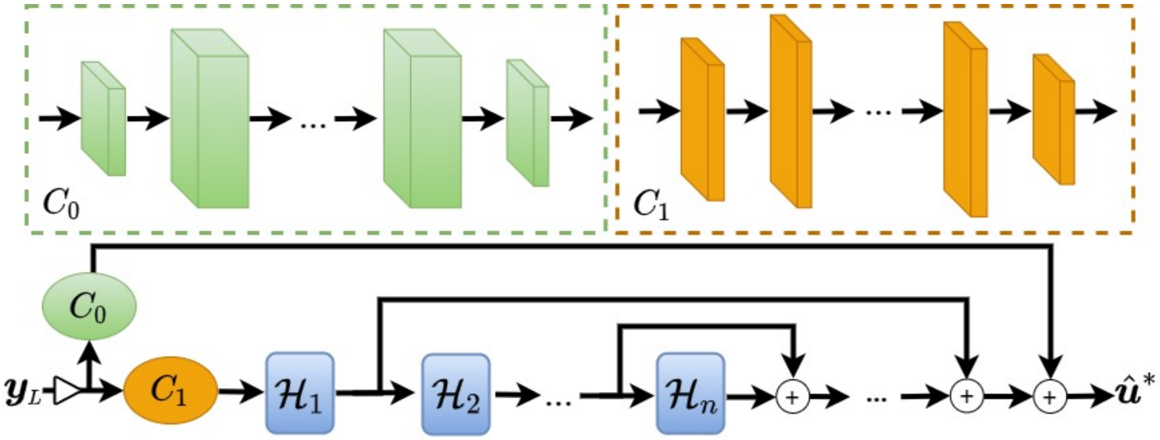


- Low-pass filtering
- Adaptive filtering
- Input structure design

our neural network structure



Our unified learning-based framework



$$y_L = [\hat{u}_L^t, \hat{u}_L^{t-1}, \gamma]$$

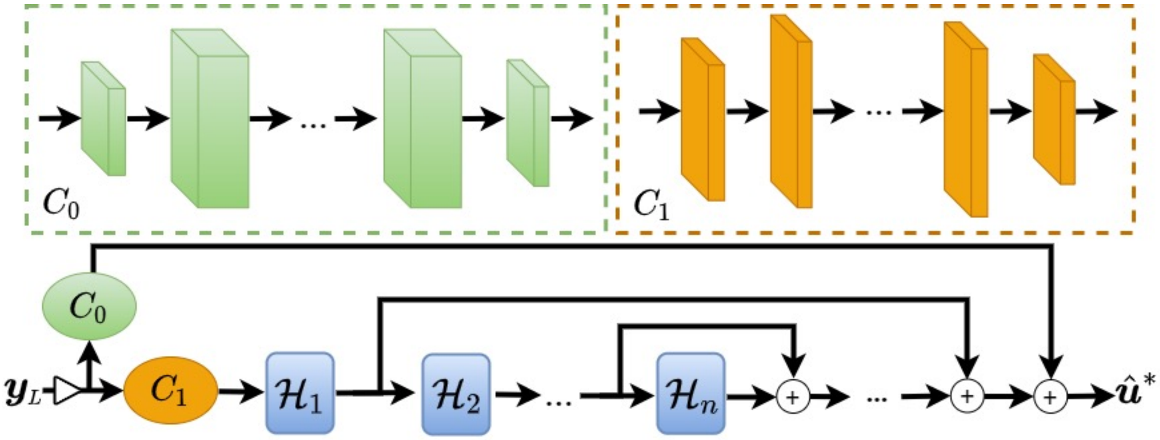
(input vector $\gamma \in [0,1]$)

Our learning-based framework can handle *both* spatial and temporal upsampling of high-res turbulent flows.

Training and applications

VELOCITY FIELD UPSAMPLING

Training for spatial upsampling



$$y_L = [\hat{u}_L^t, \hat{u}_L^{t-1}, \gamma]$$

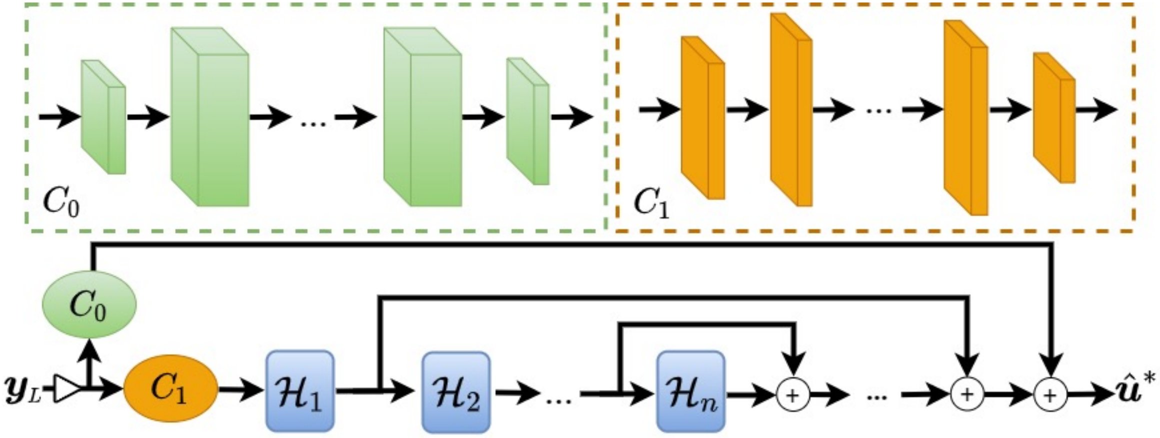
Input: Gaussian filtered downsampled input

Output: upsampled high-res

Time code: γ=1

VELOCITY FIELD UPSAMPLING

Training for temporal upsampling



$$y_L = [\hat{u}_L^t, \hat{u}_L^{t-1}, \gamma]$$

Input:
low frame rate input

Output:
intermediate frames

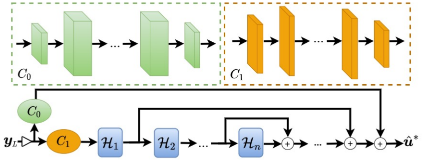
Time code: $\gamma \in [0,1]$

Spatio-temporal upsampling

low frame rate
coarse input

spatial upsampling

low frame rate
upsampled output

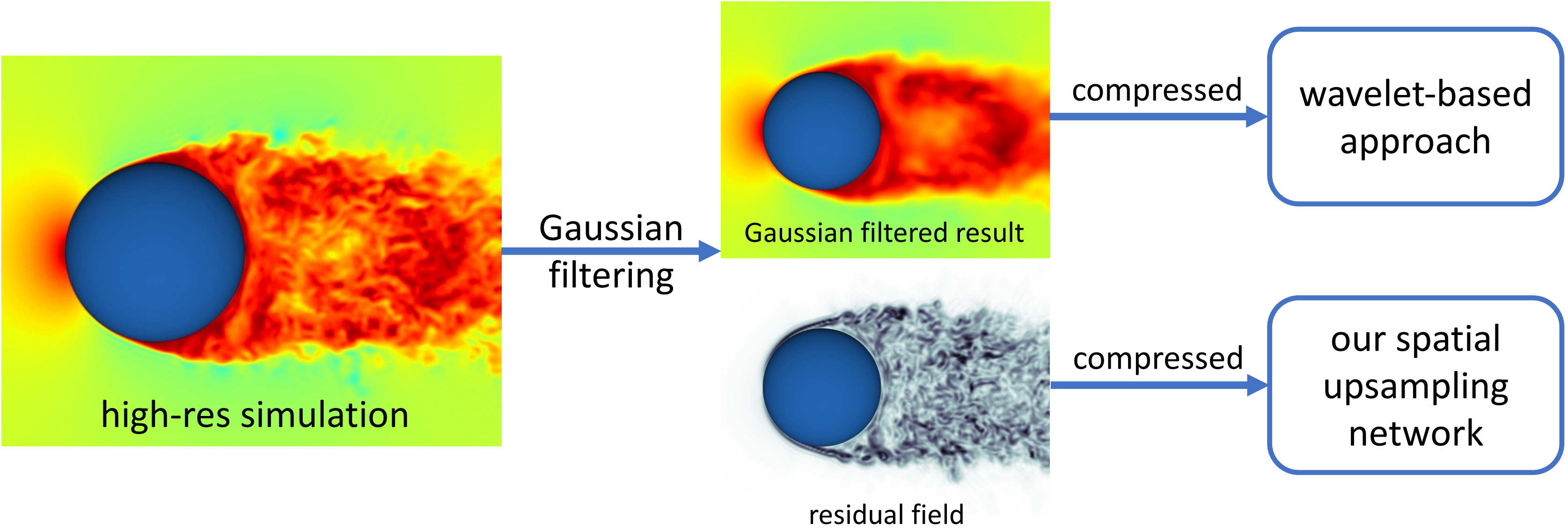


temporal upsampling

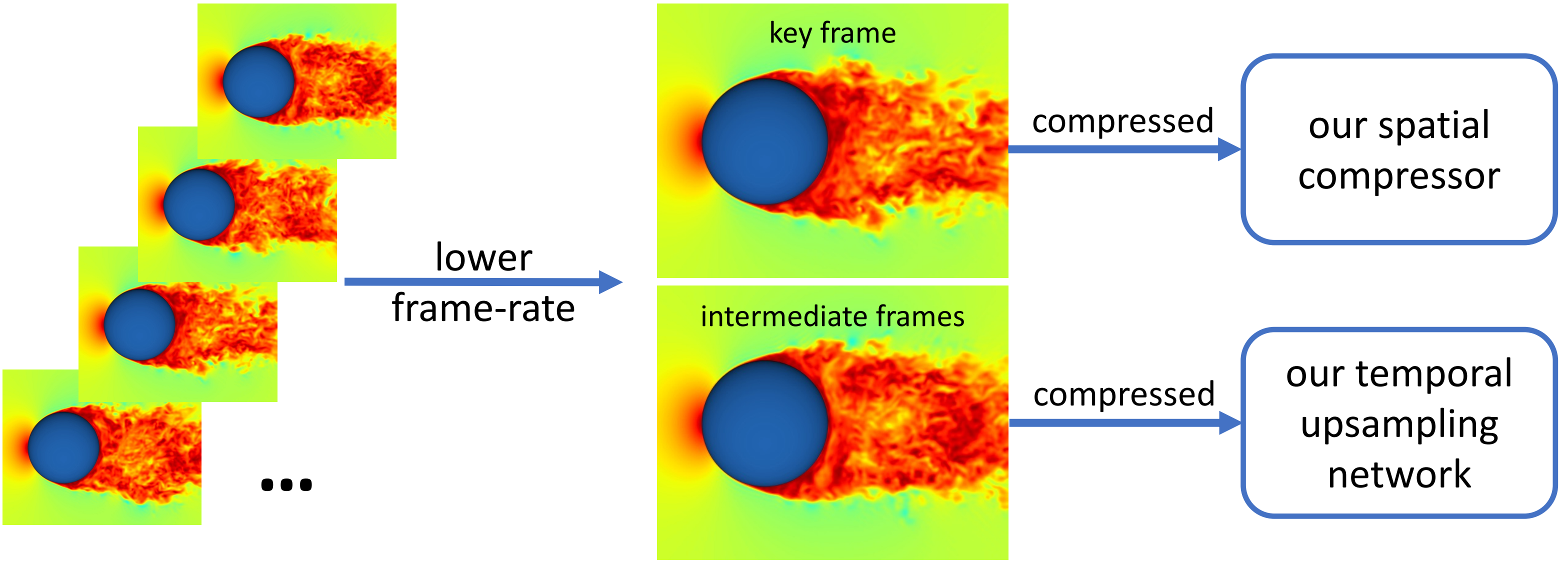
higher frame rate
upsampled output

The two upsampling processes are independent.

Patch-based compressor (in space only for now)

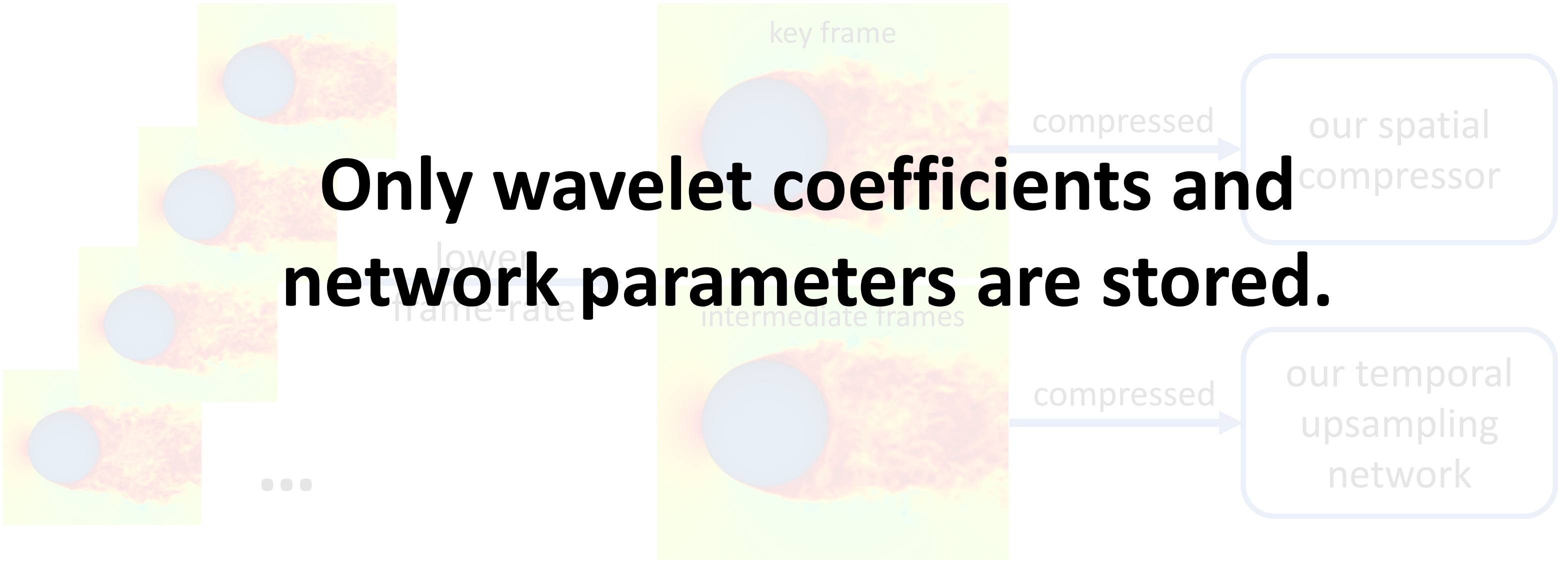


Time-varying flow field compression



FLUID DATA COMPRESSION

Time-varying flow field compression



Only wavelet coefficients and network parameters are stored.

Results

RESULTS: Unique Training Set

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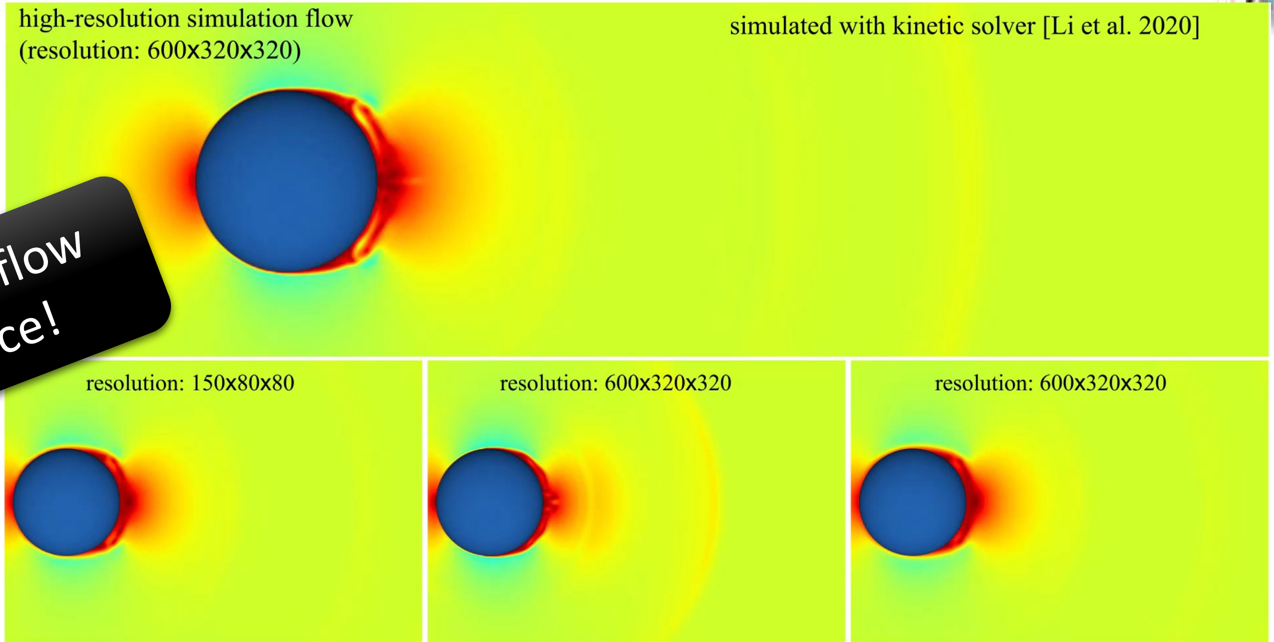
Training set

Note: we use a single flow simulation sequence!



down-sampled input used to train spatial upsampling

low frame-rate input used to train temporal upsampling

Gaussian filtered input used to train codec

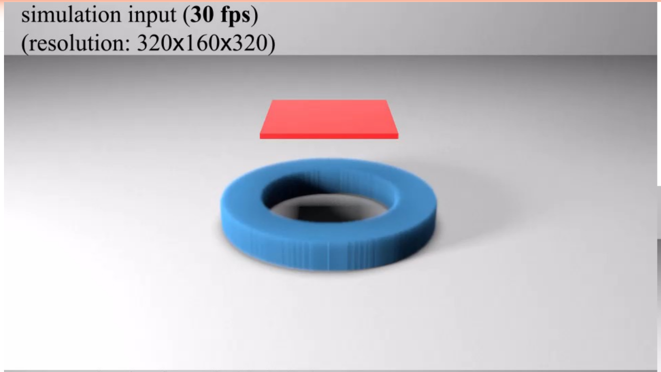
RESULTS: Spatial Super-Resolution

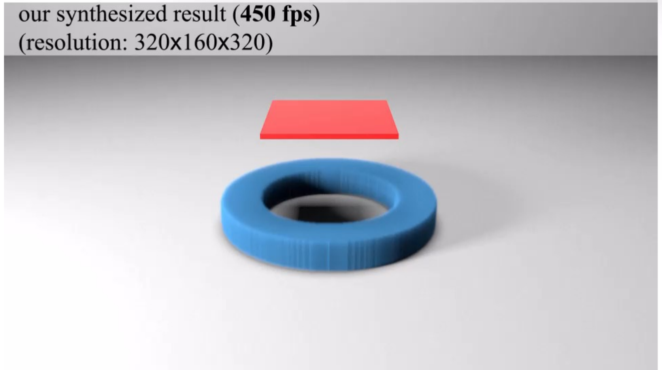
RESULTS: Spatial Upsampling

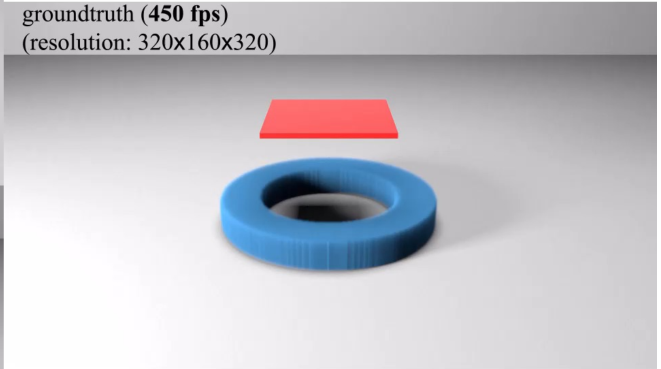
low-resolution simulation input
(resolution: 250x100x100)

our synthesized high-resolution flow
(resolution: 1000x400x400)

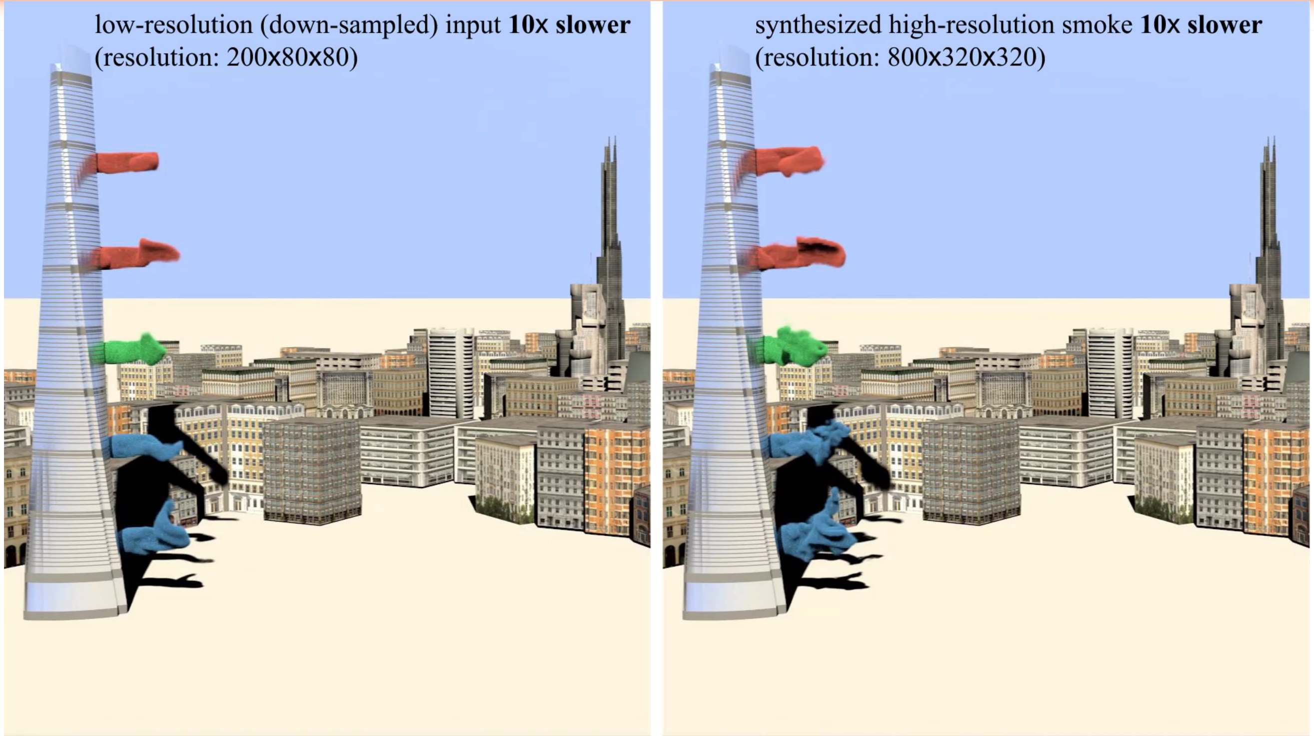
RESULTS: Temporal Upsampling



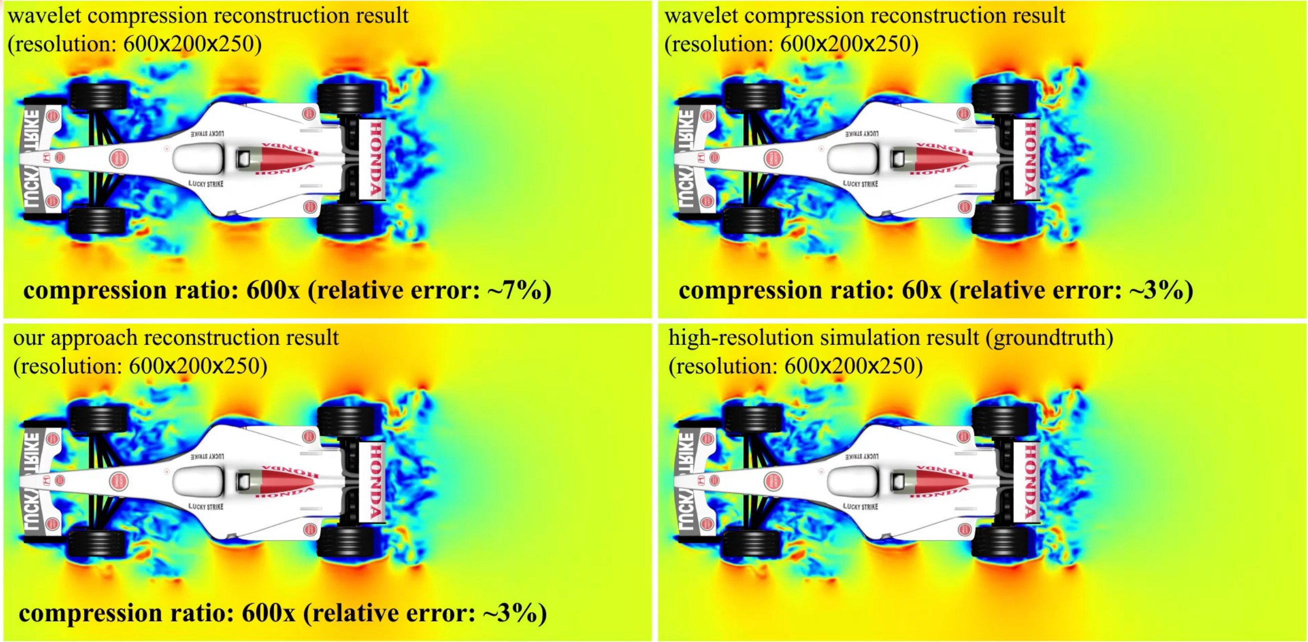




RESULTS: Space-Time Upsampling



RESULTS: Compression



Compared with wavelet compression, our approach could achieve a 10x improvement in compression ratio.

Discussions

DISCUSSIONS

Generalizability

- Additional filtering to reduce aliasing artifacts
- Training from a very limited training set is enough
- Temporal upsampling is more challenging than spatial upsampling

DISCUSSIONS

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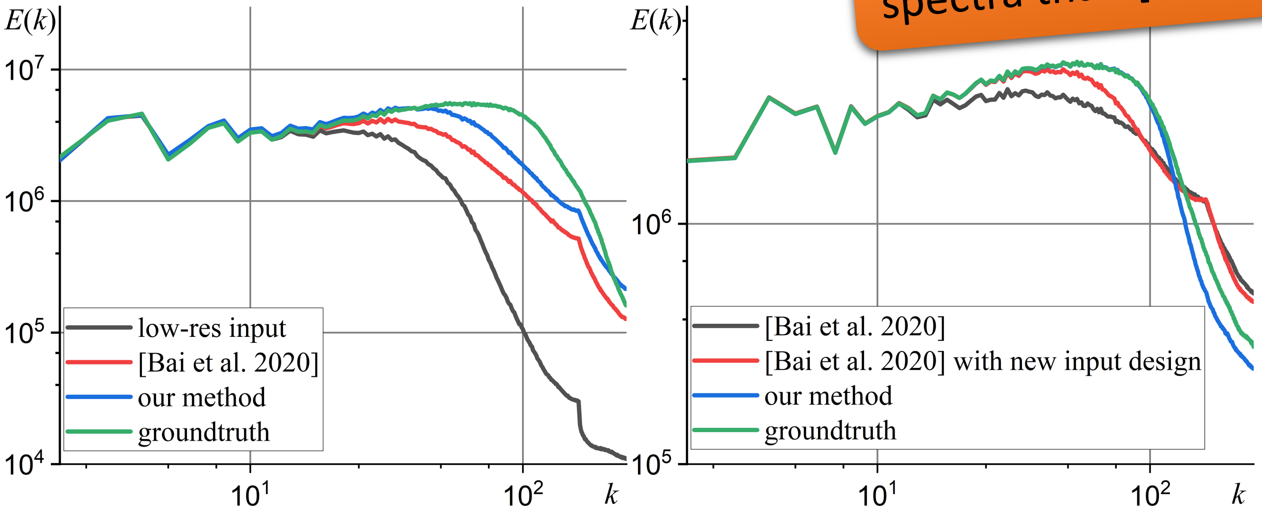
Prediction accuracy

Our network produces better spectra than [Bai et al. 2020].



spatial super-resolution

temporal upsampling

DISCUSSIONS

Performance

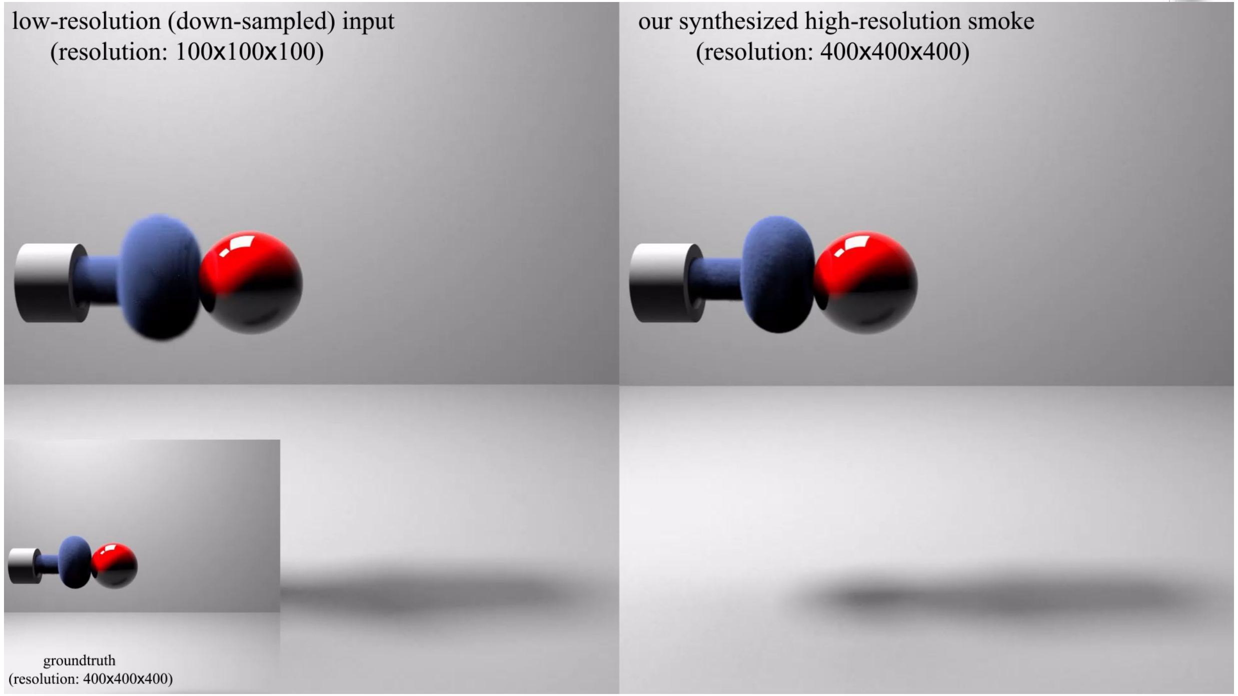
Figs	input type	σ	k	input resolution	output resolution	Re	low-res preparation time	high-res simulation time	prediction time	speed-up
Fig. 1	low frame rate downsampled input	1.4	10	200×80×80	800×320×320	50,000	n/a	256.9 sec.	44.3 sec.	5.8
Fig. 6	downsampled input	1.4	n/a	150×80×80	600×320×320	20,000	n/a	170.4 sec.	33.9 sec.	5.0
Fig. 7	low frame rate input	0.0	10	320×480×320	320×480×320	20,000	n/a	140.6 sec.	28.5 sec.	4.9
Fig. 9 (left)	Gaussian filtered input	2.0	n/a	600×320×320	600×320×320	4,000	n/a	170.4 sec.	33.9 sec.	5.0
Fig. 9 (middle)	Gaussian filtered input	2.0	n/a	600×320×320	600×320×320	20,000	n/a	170.4 sec.	33.9 sec.	5.0
Fig. 9 (right)	Gaussian filtered input	2.0	n/a	600×320×320	600×320×320	100,000	n/a	170.4 sec.	33.9 sec.	5.0
Fig. 8	downsampled input	1.4	n/a	180×60×60	720×240×240	20,000	n/a	154.1 sec.	20.4 sec.	7.6
Fig. 10	low-res simulation input	4.0	n/a	250×100×100	1000×400×400	50,000	6.1 sec.	678.3 sec.	93.2 sec.	6.8
Fig. 11	low frame rate input	0.0	15	320×160×320	320×160×320	30,000	n/a	59.7 sec.	6.8 sec.	8.8
Fig. 13	low frame rate Gaussian filtered input	2.0	10	600×200×250	600×200×250	100,000	n/a	93.5 sec.	13.7 sec.	6.8

Our approach can achieve 5x-10x faster than the corresponding high-res simulation.

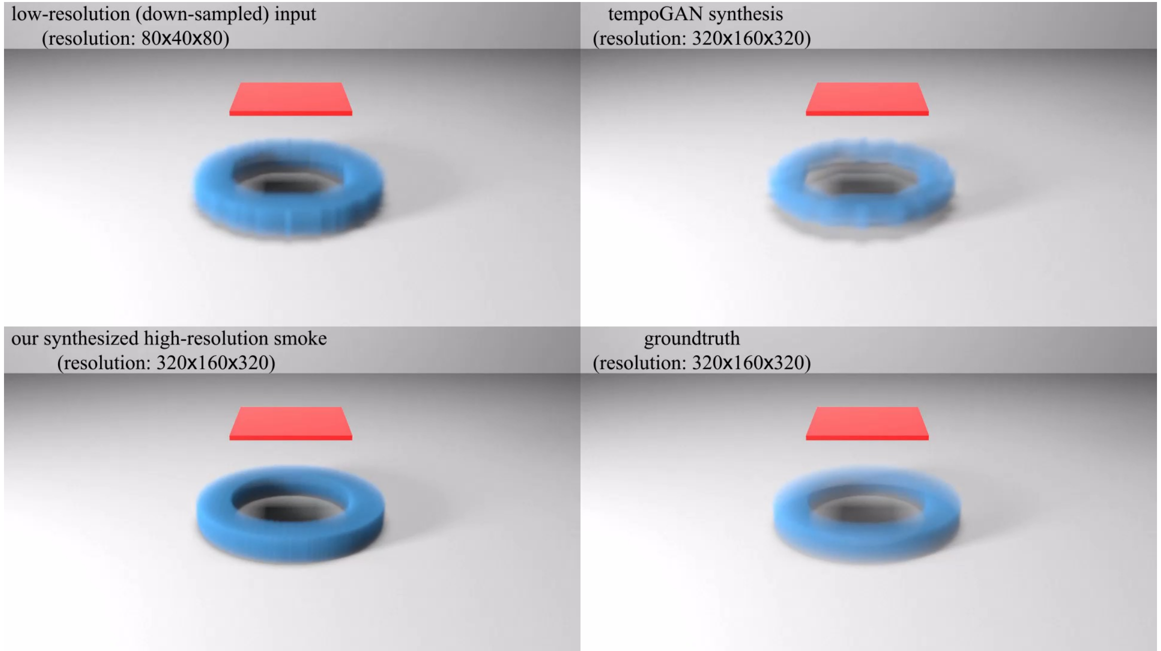
DISCUSSIONS

Applicability to other fluid solvers

Reflection-advection MacCormack solver



Comparison with tempoGAN [Xie et al. SIGGRAPH 2018]



LIMITATIONS

- Temporal synthesis still exhibits only relatively limited generalizability when trained on limited examples
- We cannot ensure physical accuracy
- Not enough dictionary patches may lead to bad “extrapolation”

CONCLUSION

- **A simple and effective learning-based approach**
  - predicting turbulent flow details in space and time
- **An adaptive filtering strategy with new input design**
  - that is more generalizable for both space and time upscaling
- **A unified framework for spatio-temporal upsampling**
  - offering a wide range of applications

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EXHIBITION 15 - 17 DECEMBER 2021
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THANK YOU!

Presented by: Kai BAI