Deep learning based spatio-temporal interpolation in fluid dynamics

USC Viterbi School of Engineering

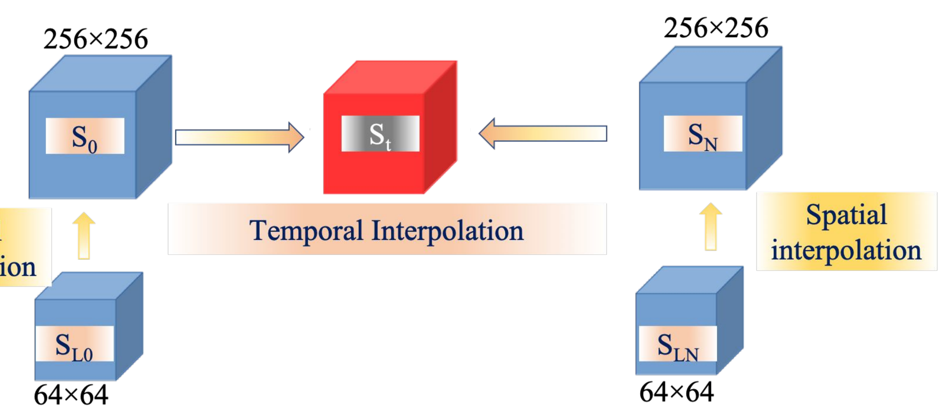
Xiangyu Gao, Jun Luo, Harsh Mohan, Subodh C. Tiwari, Ziqi Zeng

Team: Mom tells me the professor doesn't like long names

Introduction

Fluid dynamics simulations are **computationally expensive** and **require massive storage.**

- Datasets saved are often **temporaly coarse.**
- **Massively parallel computation** needed for simulation.

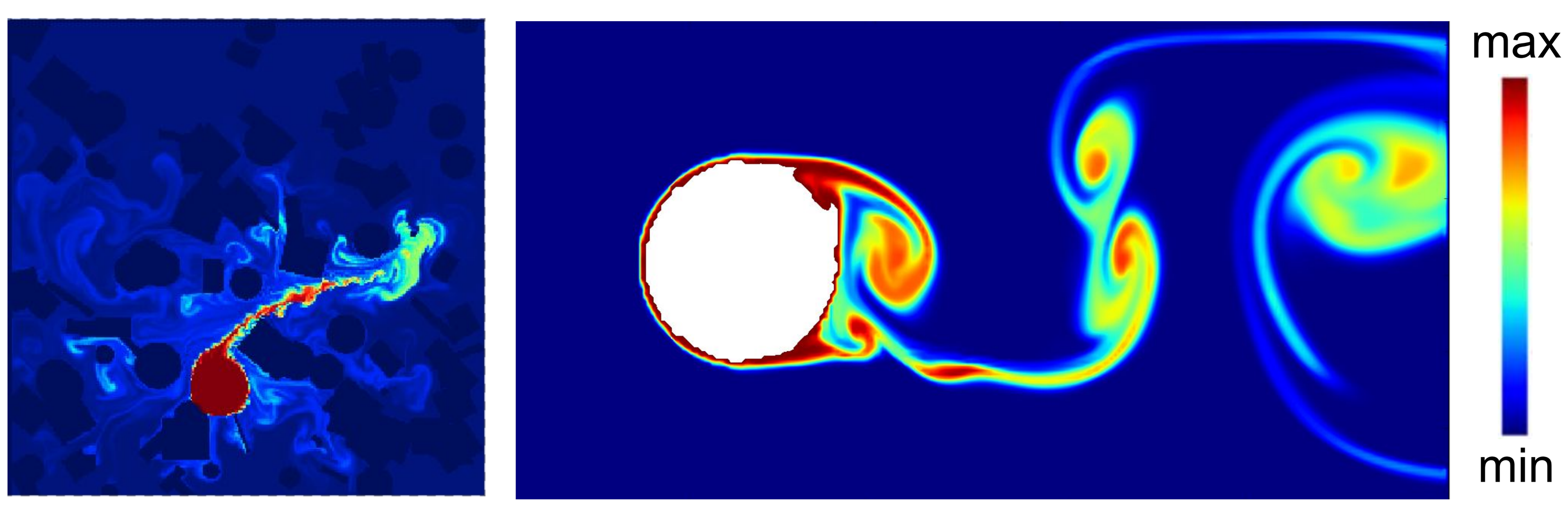


Solution:

Use **spatial and temporal interpolation** to re-generate fine-grain data from coarse grain-data

Dataset

Deep-learning models require large, diverse datasets across several physical scenarios. Currently, the interpolation is performed only on the density field. We **write our own simulations** using an open source solver, **MantaFlow.** We generate **40,000+ data points** across two types of scenes - Plume and Karman Vortex Street.

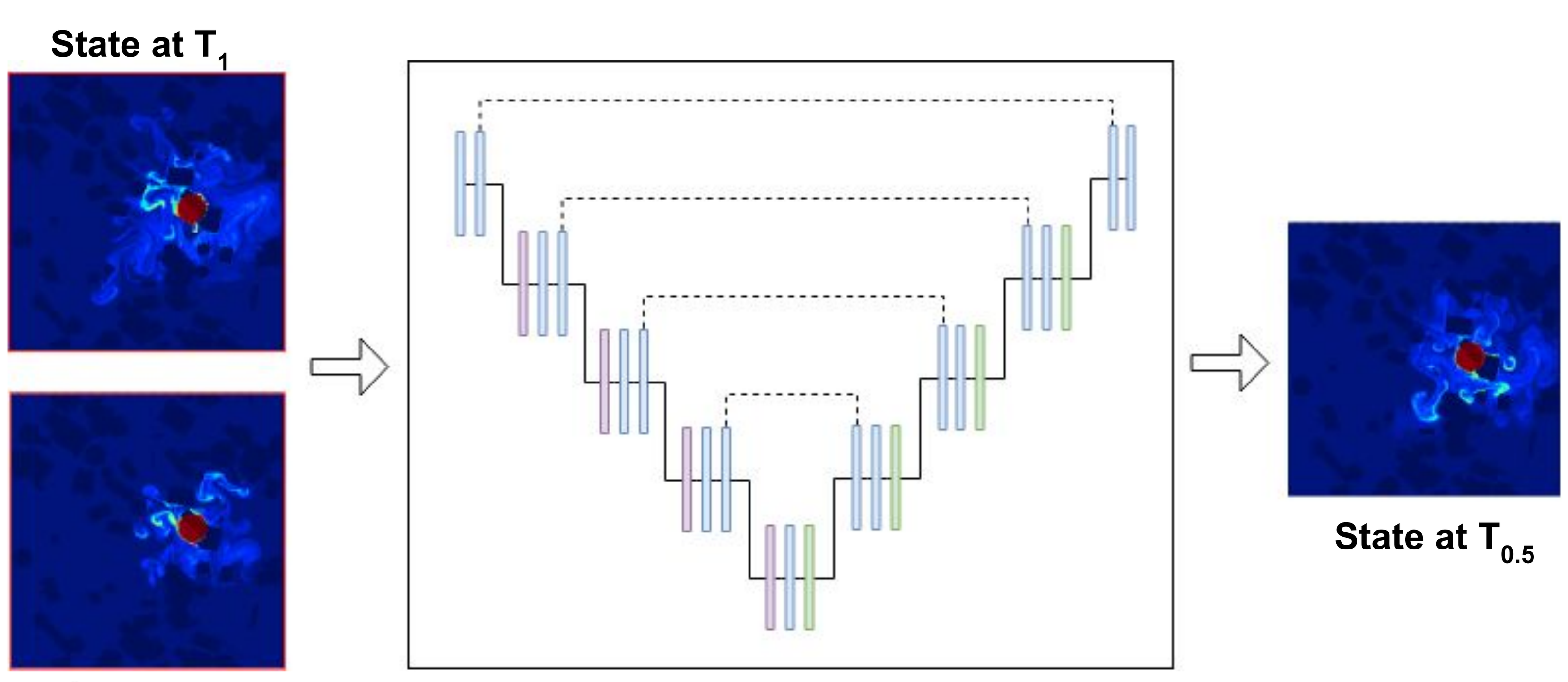


Density field of 2D Plume (left) and Karman Vortex Street (right)

Models

Temporal Interpolation

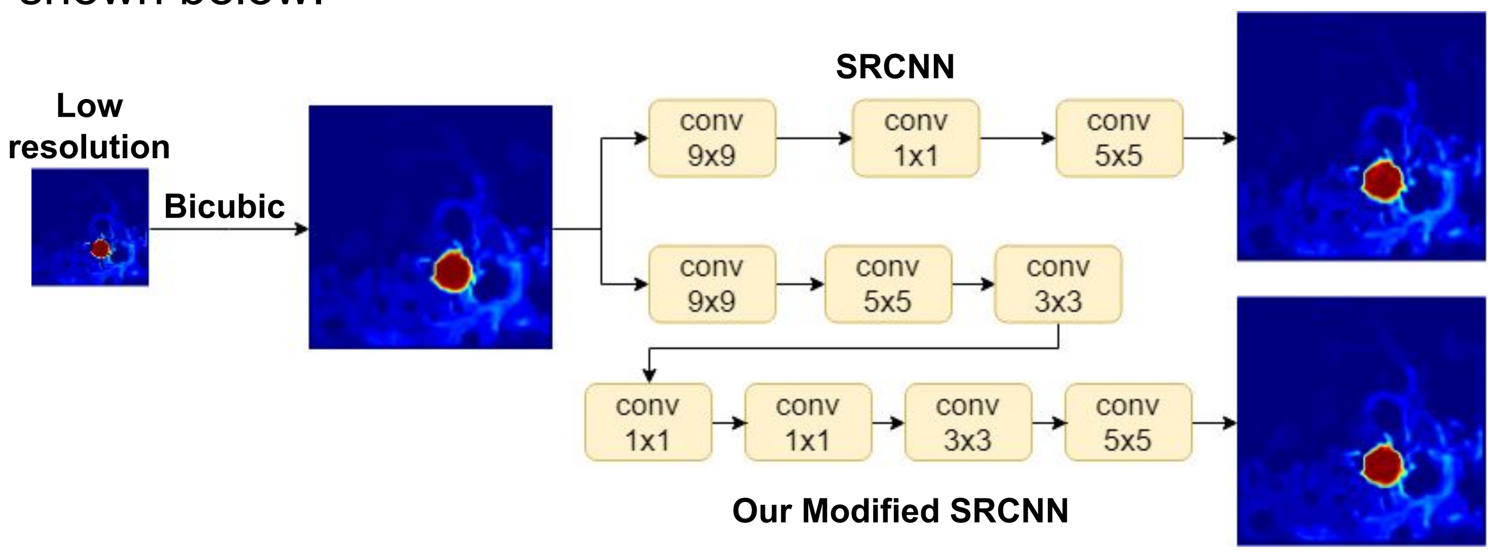
Temporal interpolation network is inspired from a state-of-the-art video-frame interpolation method **SuperSloMo** with a few changes to accommodate fluid data. Most notablly, we avoid computing the optical flow and fix timestep interpolation at 0.5. A summary of our model can be seen below.



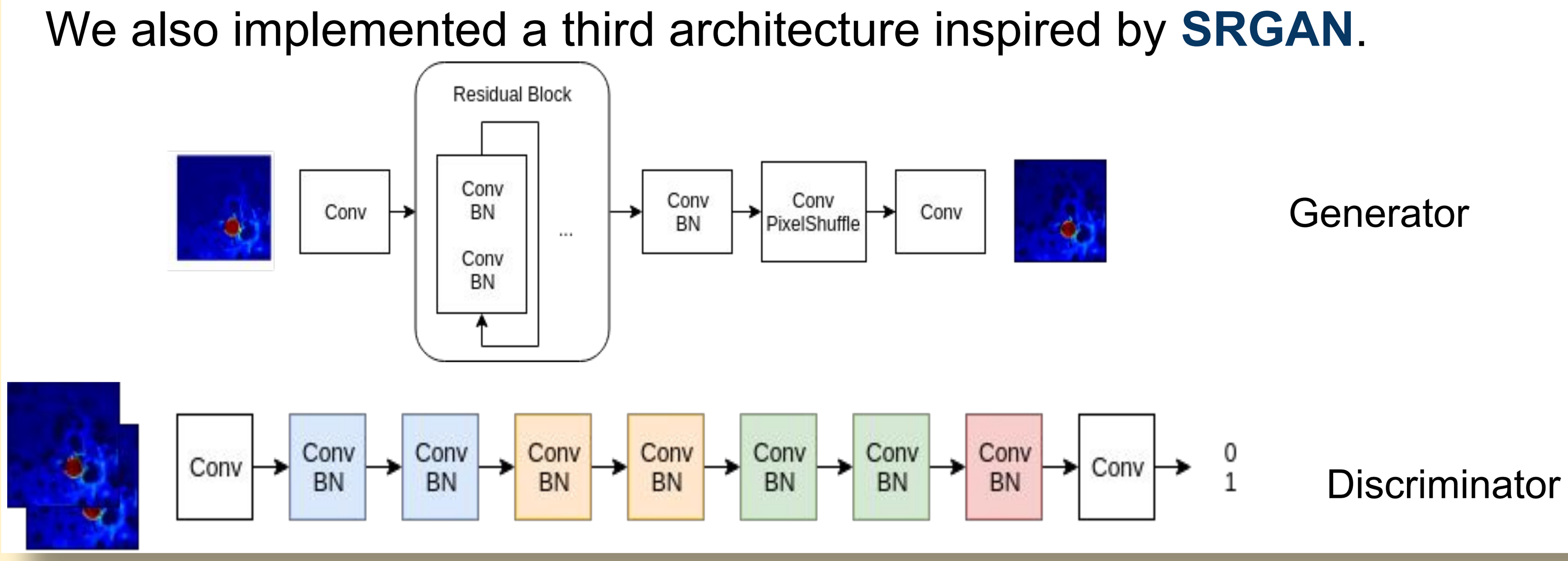
SuperSloMo-Frame interpolation module (U-net Backbone)

Spatial Interpolation

We implemented and compared two deep learning architectures inspired by **SRCNN** -- the vanilla SRCNN and our improved modified SRCNN (DSRCNN). A detailed comparison of these two models are shown below.



We also implemented a third architecture inspired by **SRGAN**.

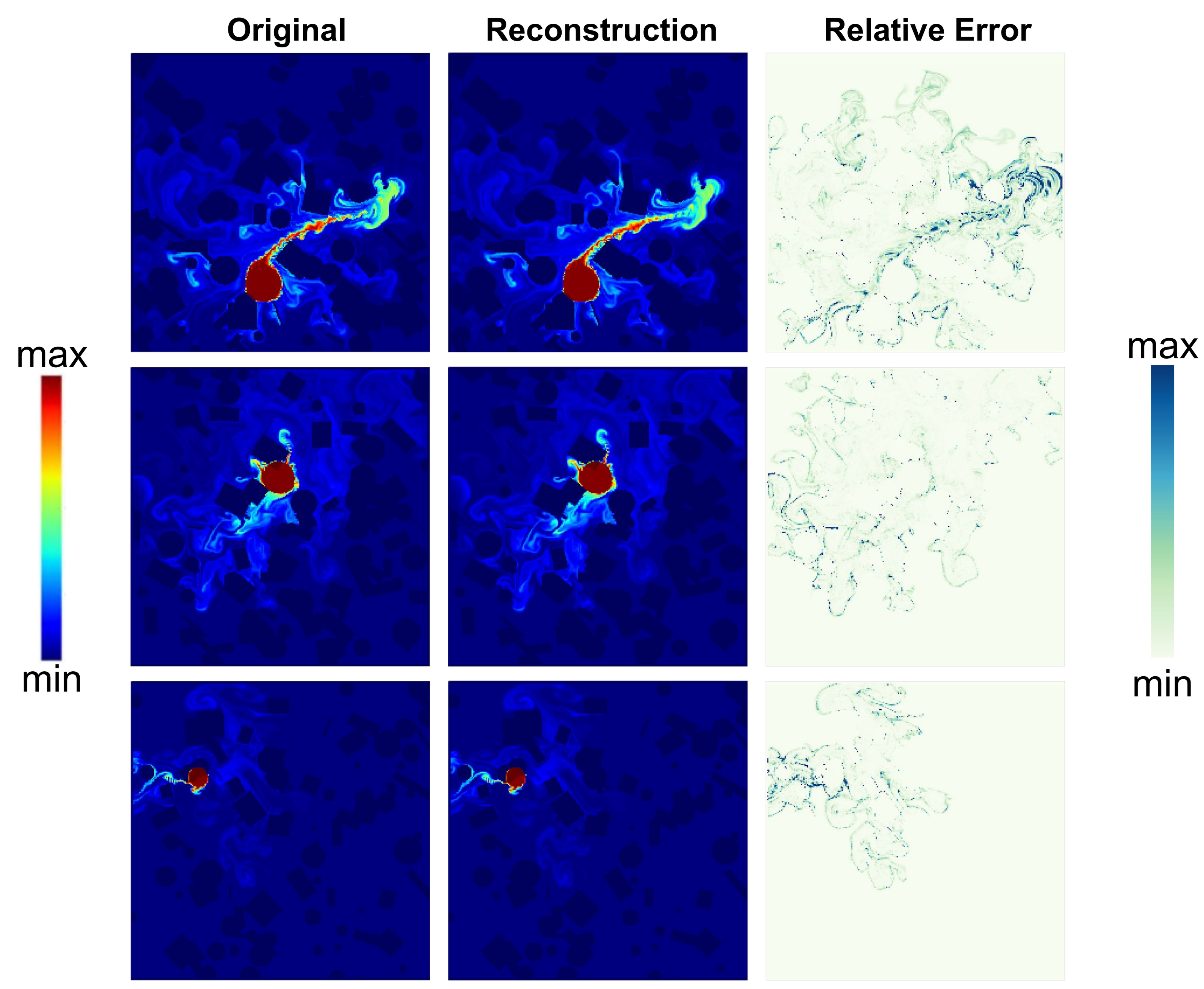


Results

Temporal Interpolation

Based on our experimentation, our model is able to reconstruct the simulations fairly well. Besides this, our model also proved to be **30-60 times faster** depending on the complexity of the simulation. A summary of our results and some reconstructions can be seen below.

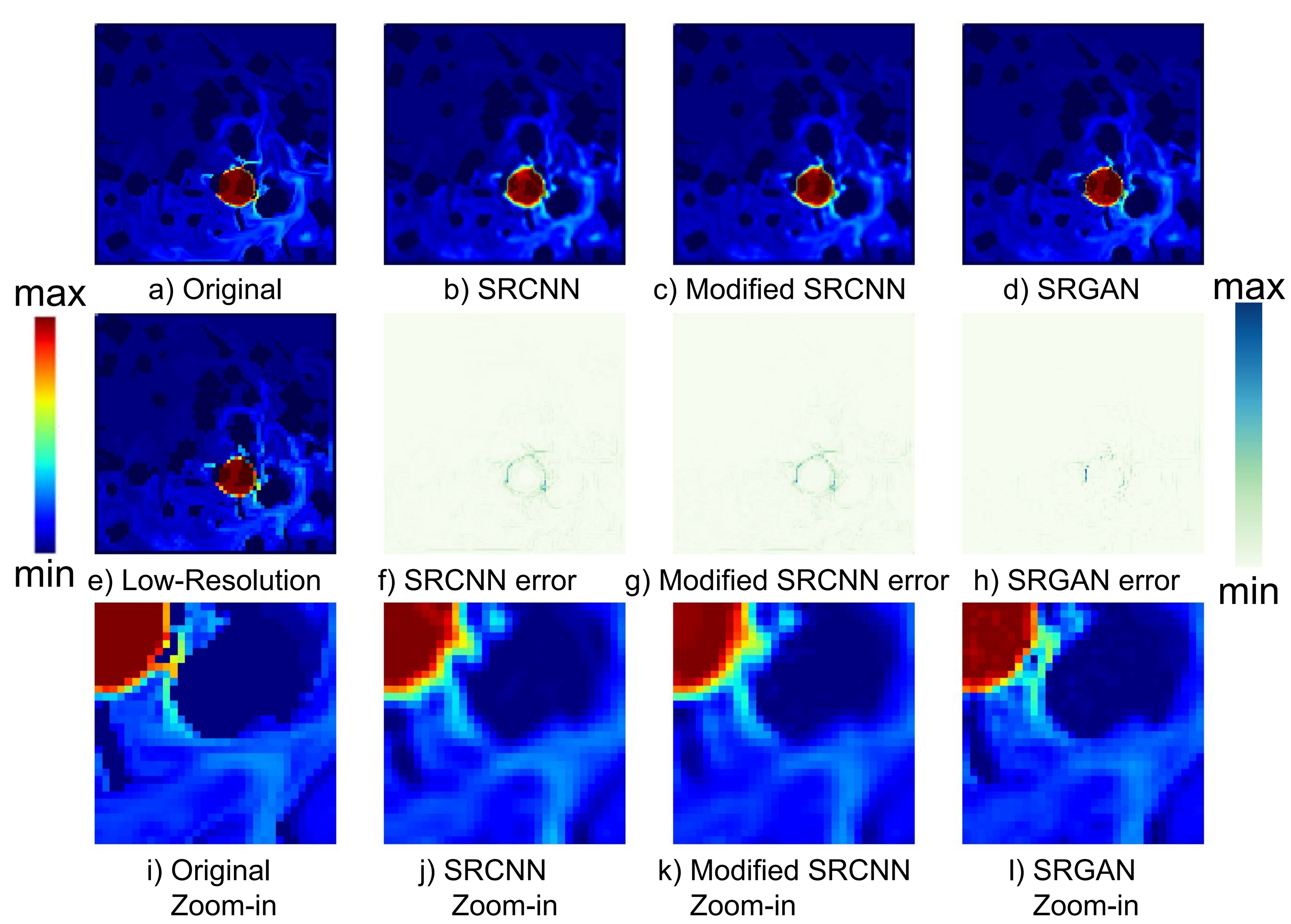
Model / Reconstruction	Mean absolute error	Mean relative error
Base - 1 frame window	**0.00080**	**3.37%**
Base - 2 frames window	0.0018	7.79%
Base - 3 frames window	0.0030	12.68%



Spatial Interpolation

The reconstruction results of all three spatial models are reasonable. The SRGAN model turns out to have the smallest reconstruction loss among the three. Our improved modified SRCNN comes second. A summary of the results is shown below.

Model	Mean absolute error	Mean relative error
SRCNN	0.0018	15.23%
Modified SRCNN	0.0014	12.47%
SRGAN	**0.0006**	**11.52%**



Conclusion

We have created a novel way to compress data and accelerate fluid dynamics simulations using spatial and temporal interpolation.

Future Work

- Experiment with continuous filter convolutional neural networks.
- Improve Navier-Stokes constraints loss term implementation.
- Experiment and train on several other physical phenomena.

Source code: https://gitlab.com/f1recracker/csci599-fluid-state-prediction