High-Fidelity Wind Turbine Wake Prediction through CNN-based Super Resolution Techniques

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Abstract

We present a novel approach to high-fidelity wind turbine wake prediction using convolutional neural networks (CNN)-based super-resolution techniques.

Wind turbine wakes, which significantly impact the efficiency and lifespan of downstream turbines, have traditionally been challenging to model accurately due to their complex, dynamic nature. By employing CNNs to enhance low-resolution computational fluid dynamics (CFD) simulations, our method substantially improves the spatial resolution and predictive accuracy of wake profiles.

This advancement allows for more precise predictions of wake characteristics, such as velocity deficits and turbulence intensity, over a range of atmospheric conditions.

High-Fidelity Simulation (LES)

Large Eddy Simulation (LES) is used to simulate the detailed turbulent flow structures in the wind turbine wakes. LES solves the filtered Navier-Stokes equations:

- $\partial_i \bar{u}_i = 0$
- $\partial_t(\rho\bar{u}_i) + \partial_j(\rho\bar{u}_i\bar{u}_j) = -\partial_i\bar{p} + 2\partial_j(\mu\bar{S}_{ij}) - \partial_j(\tau_{ij})$
- $\bar{S}_{ij} = \frac{1}{2}(\partial_i\bar{u}_j + \partial_j\bar{u}_i)$
- $\tau_{ij} = \rho(\overline{u_i u_j} - \bar{u}_i\bar{u}_j)$

- $\bar{u}_i$ is the filtered velocity.
- $\bar{p}$ is the filtered pressure.
- ρ is density.
- μ is molecular viscosity
- $\bar{S}_{ij}$ is the filtered, or resolved scale strain rate tensor
- τ_{ij} is the sub-grid scale stress tensor.

CNN-based Super Resolution Technique

CNN Architecture:
- Input Layer: Low-resolution CFD data.
- Convolution Layers: Multiple layers with ReLU activation functions to extract features.
- Upsampling Layers: To increase the resolution of the feature maps.
- Output Layer: High-resolution wake prediction.

Equation:
The CNN model can be mathematically described by the following function:

$$\hat{Y} = f(\boldsymbol{X};\theta)$$

- $\boldsymbol{X}$ represents the input low-resolution data.
- θ represents the learnable parameters of the CNN.
- $\hat{Y}$ represents the output high-resolution data.

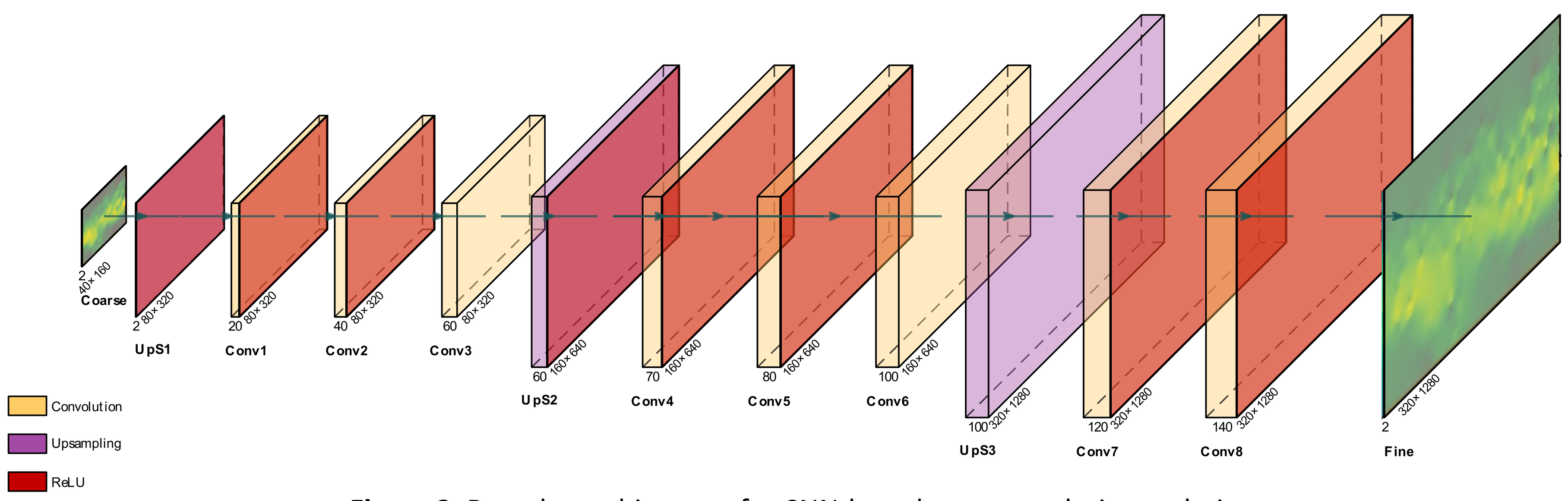

Figure 2: Decoder architecture for CNN-based super-resolution techniques

Discussion

Our approach demonstrates a significant improvement in the prediction of wind turbine wakes, which can lead to better design and optimization of wind farms. Future work will focus on further refining the model and exploring its application to other types of fluid dynamics problems.

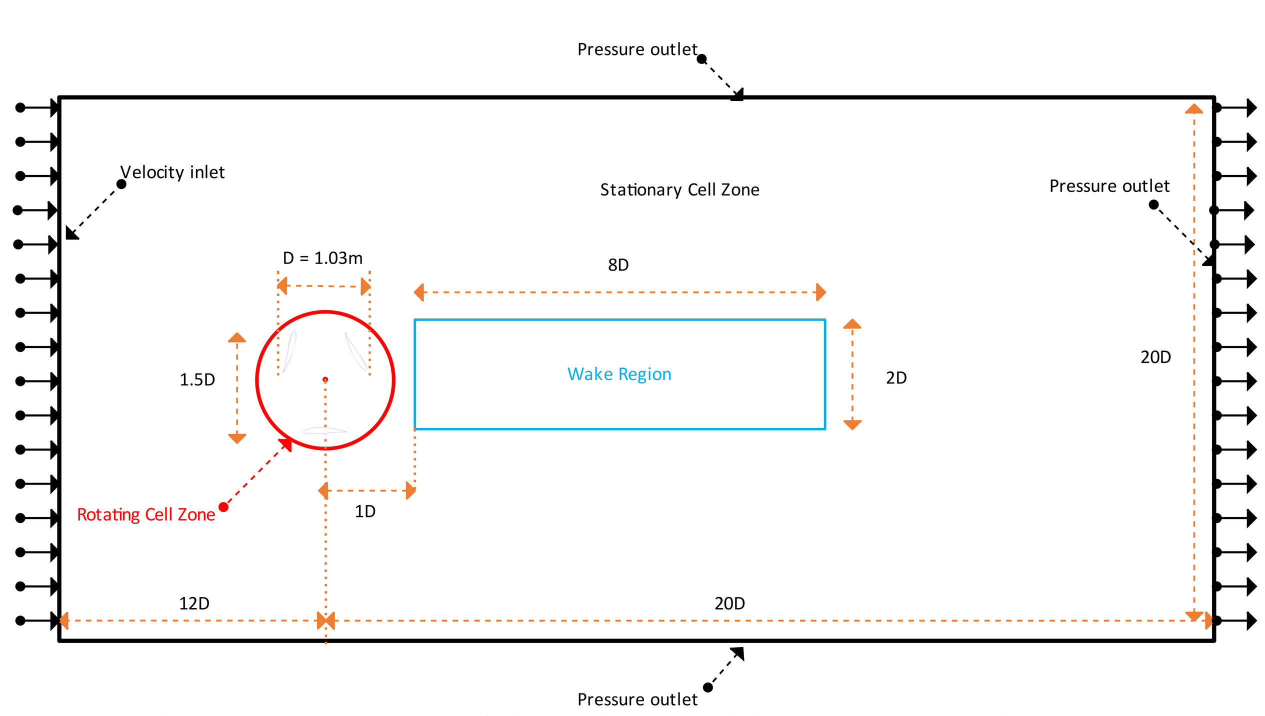

Figure 1: Dimensions of the cell zones of the computational domain

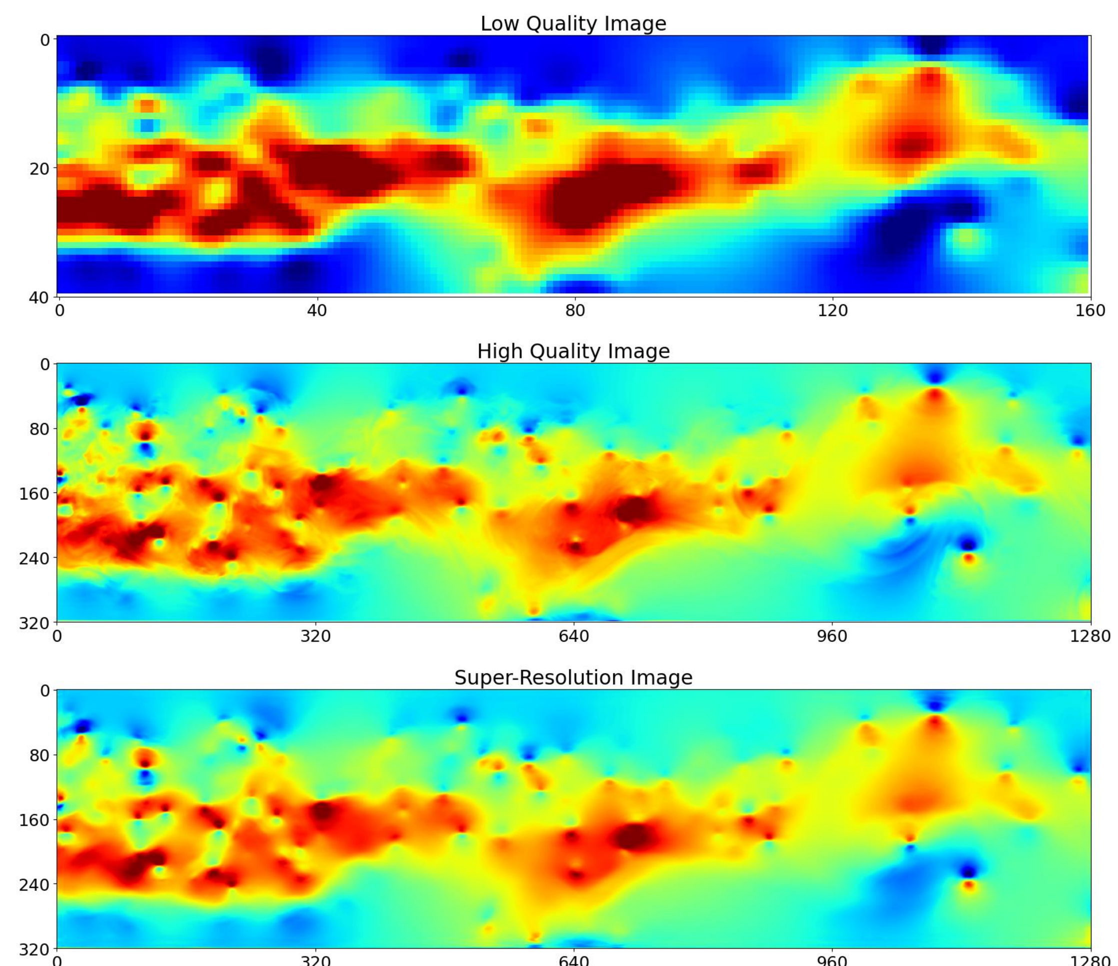

Figure 3: Comparison of x-velocity fields at timestep 1300 for low-resolution CFD, high-resolution CFD, and super-resolution

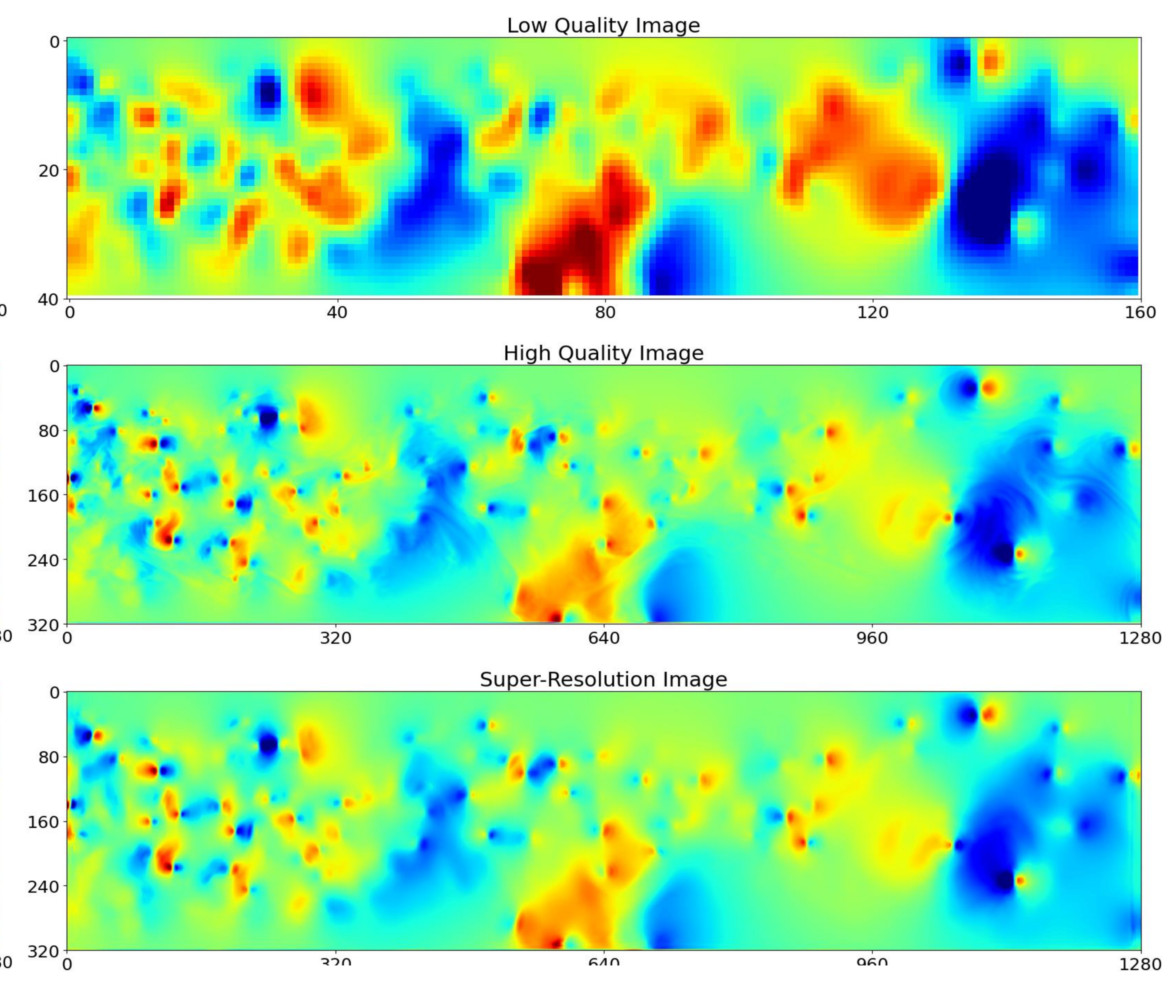

Figure 4: Comparison of y-velocity fields at timestep 1300 for low-resolution CFD, high-resolution CFD, and super-resolution image

Results

Applying the CNN-based super-resolution technique has substantially improved the spatial resolution and predictive accuracy of wake profiles. The results show enhanced x-velocity and y-velocity predictions that closely match high-resolution LES data.

Figure1: Dimensions of the cell zones of the computational domain
Figure2: Decoder architecture for CNN-based super-resolution techniques
Figure3: Comparison of x-velocity fields at timestep 1300 for low-resolution CFD, high-resolution CFD, and super-resolution image
Figure4: Comparison of y-velocity fields at time steps 1300 for low-resolution CFD, high-resolution CFD, and super-resolution image
Figure5: Super-resolution error over time for x-velocity and y-velocity components during training and testing phases.

Figure 5: Super-resolution error over time for x-velocity and y-velocity components during training and testing phases.

Conclusion

Our method shows a notable enhancement in predicting wind turbine wakes, potentially resulting in improved design and optimization of wind farms.

The error percentage shown in Figure 5 remains consistently low, indicating the effective performance of the super-resolution model.

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