Super-resolution analysis with machine learning for low-resolution flow data

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In recent years, numerous applications of machine learning for fluid dynamics have been proposed for turbulence modeling, reduced order modeling, and flow control. These applications show remarkable capabilities of machine learning techniques due to their ability to handle big fluid flow data containing strong nonlinear and chaotic characteristics (Kutz, 2016). In the present study, machine-learned super-resolution analysis, known as a powerful tool to reconstruct the high-resolution signal from the coarse signal in image tasks, is applied for fluid flow data.

We use the bicubic interpolation (Keys, 1981) known as the traditional super-resolution method in image tasks and the convolutional neural network (CNN) (LeCun et al., 1998) for machine-learned super-resolution technique in image tasks, as the first trial. Although both reconstructed results show reasonable agreement with the reference high-resolution data, these methods cannot reconstruct the high-resolution flow field from very coarse data. Hence, we consider the use of the hybrid Downsampled Skip-Connection Multi-Scale (DSC/MS) model to process multi spatial scales of flow data. In the current work, the high-resolution data sets for training/validation and test are obtained by direct numerical simulation (DNS). The coarse data sets are made by max and average pooling operation used widely in image processing.

First, we use a machine-learned technique to reconstruct the high-resolution flow field from the low-resolution data of two-dimensional cylinder wake (Taira and Colonius, 2007; Colonius and Taira, 2008) and the NACA0012 airfoil wake (Gopalakrishnan Meena et al., 2018), as preliminary tests. In the example of laminar cylinder wake, the reconstructed flow field by machine-learned super-resolution technique shows reasonable agreement with the reference DNS data in terms of the distribution of the vorticity field ω, the L_2 error norms, and probability density function of the vorticity field. We then apply the machine-learned super-resolution analysis to a more dynamically rich problem of two-dimensional flow over a NACA0012 airfoil with a Gurney flap. By adding a Gurney flap to the NACA0012 airfoil, various wakes patterns emerge depending on the angles of attack α and the Gurney-flap height h/c. We use $\alpha = 3^\circ, 12^\circ$ and 20° with $h/c = 0.1$ to examine three different wake regimes. In all cases, the reconstructed fields show good agreement with the reference DNS data as with the cylinder example. Moreover, we also confirm the relationship between an accuracy of machine-learned models and the unsteadiness in the wakes.

Next, two-dimensional decaying isotropic turbulence (Taira et al. 2016) is considered to demonstrate the strength of machine-learned super-resolution analysis for turbulent flows. We use a variety of low-resolution data sets obtained by max and average pooling operation: medium resolution, low resolution and super-low resolution, respectively. The machine-learned model is able to reconstruct the flow field in terms of the distribution of the velocity field, the L_2 error norms and the kinetic energy spectra over the spatial wavenumber k. In particular, the high-resolution flow field (128×128 pixels) are recovered from as little as 4×4 pixels using the hybrid DSC/MS model. Regarding the kinetic energy spectra, the recovery ratio of wavenumber can be approximately four fold with max pooling operation by the hybrid DSC/MS model. For the average pooled input data, we can achieve over two fold. These observations suggest the possibility of an application for large eddy simulation subgrid-scale modeling and enhancement of PIV measurements. For details, we refer the readers to Fukami et al. (2018) for further discussions on machine-learned super-resolution analysis for turbulent flows, i.e., the choice of other input and output attributes, the dependence of the number of the training data snapshots and the computation time for constructing machine-learned models are reported therein.

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