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Nonlinear Dimensionality Reduction for Three-dimensional Flow Field Around Circular Cylinder with Distributed Parallel Machine Learning on Fugaku

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POD (Proper Orthogonal Decomposition) is the typical method for reducing the flow field system's dimension [1]. However, since a linear function reduces the dimension in POD, it is known that sufficient reduction performance cannot be obtained for a flow field in which advection is predominant; that is, non-linearity is prominent [2]. Therefore, Murata et al. used a convolutional neural network (CNN) to perform non-linear dimensionality reduction for a two-dimensional flow field around a circular cylinder [3]. This study extends this idea to a three-dimensional flow field, and dimensionality reduction is performed by a massively parallel distributed machine learning on Fugaku.

As a result, it was confirmed that if the time interval of the flow field snapshot data to be learned can be sufficiently small to resolve the oscillation with a short cycle, the reduction performance of the detailed vortex structure of the flow field improves as the number of network parameters is increased. In addition, it was confirmed that the computational performance of our method scales well to about tens of thousands of nodes (i.e., millions of cores) on Fugaku by increasing the number of network parameters.

Based on the above results, our method indicates the possibility that the dimension of the complex vortex structure and short cycle oscillation of a three-dimensional fluid can be reduced with sufficient accuracy by adjusting the time-resolution of the learning data and increasing network parameters. In the future, we would like to increase the scale of distributed learning further and aim to improve the reduction performance required for the high-resolution three-dimensional flow field.

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