Prediction of the high-resolution numerical flux by using a deep neural network

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Magnetohydrodynamic simulations have played important roles for understanding space and astrophysical phenomena. In such circumstances, shock waves and turbulence are inherent properties, and both aspects equally affect evolution of the whole system. Therefore development of numerical algorithms capable of solving both shock waves (discontinuities) and turbulence (waves) with high resolution is a challenging task to tackle violent phenomena in space and astrophysical plasmas.

High-order (greater than the fifth) spatial interpolation coupled with approximate Riemann solvers is a promising solution to such problems (Matsumoto et al., 2016; Minoshima, Miyoshi, Matsumoto, 2019). CANS+ (Matsumoto et al., 2016) employs the fifth order MP5 reconstruction scheme coupled with the HLLD approximate Riemann solver (Miyoshi and Kusano, 2005), and it successfully provided highly resolved solutions for both shock waves and turbulence. A drawback of adopting high-order schemes is its large and complex floating-point operations for obtaining the numerical flux at the cell surface, including minmod (with four arguments) limiters and conversion from the primitive to the characteristic variables. These numerical operations in addition to calculation of the HLLD numerical flux dominated overall computational loads.

In this paper, we propose a different way of calculating the numerical flux by adopting supervised learning algorithms. A deep (multilayer) neural network consists of input and output layers, whose sizes are determined by the problem of interest, and arbitrary numbers and sizes of hidden layers. These layers are connected by linear operations followed by a mapping through nonlinear functions such as a sigmoid function (fully connected networks). Weighting parameters used in the linear operations in each layer are updated repeatedly so that the loss function between the output and the label data (true value) becomes a minimum value. In the present particular problem, we prepared learning data by examining a 1-D shock tube problem which contains rarefaction waves and discontinuities by using CANS+. The input and label data are cell states for all primitive variables in six-point stencils centered on a cell and the numerical flux on the right-hand side of the cell, respectively. We have implemented a multi-layer, fully-connected network by using the Chainer framework for the prepared learning data. With the given data set we successfully obtained a network that can predict the numerical flux with 99% accuracy. In this talk we present detailed algorithms and learning data, and discuss future perspectives including application to multidimensional simulations.

Keywords: neural network, MHD simulations

