Steady Flow Prediction using Convolutional Neural Networks with Boundary Exchange

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Computational fluid dynamics (CFD) are widely used as a fluid analysis technique and various numerical methods have been developed in this field [1]. However, these have a problem that the calculation cost is very expensive and the execution time for reaching steady-state is long. To solve this problem, convolutional neural networks (CNN), which is one of the deep learning methods, is applied to CFD.

In deep learning, it is difficult to construct a large neural network due to the memory size limitation of GPU and Xeon Phi. For this reason, the size of the input data is often limited. In the previous research for image recognition, model parallel computing is adopted to handle the large-scale input data. Unlike this, we will develop a prediction method for large-scale simulation results by dividing the input geometry into multiple parts and applying a single small neural network to each part in parallel. This method is developed based on considering the characteristics of CFD simulation and the consistency of the boundary condition of each divided subdomain. In this research, we will focus on applying this method to the steady flow.

As part of the study, we first build a CNN model that predicts the results of a single region of the steady flow that is a certain fixed size. The constructed model predicts a two-dimensional velocity field using a signed distance function (SDF) as input. As a first trial, the results of two-dimensional calculations around a cylinder by lattice Boltzmann method (LBM) are used as a dataset. The training dataset contains 3,072 samples and the validation dataset contains 1,024 samples and these are different in size, shape, and location. The samples are projected into a 256×128. We compute 256×128 velocity field as labels by the LBM and calculate SDF as the input of CNN in the same area. We use a Reynolds number of 20 because this model is intended to predict the steady flow.

The model consists of input, convolution part, deconvolution part, and output [2]. Convolution part encodes the input SDF by several convolution layers. Deconvolution part is divided into two to decode the velocity in the x direction and the velocity in the y direction separately, and each consists of multiple deconvolution layers. We implement CNN using Chainer. The parameters of the networks are initialized using Xavier method in Chainer. We use Adam as optimizer with a batch size of 64 and set the learning rate to 0.0001. Figure 1 shows predicting results of our CNN model and LBM solutions. The results show that the predictions made by our model are highly accurate.

We are currently developing a method to predict a larger area than a single network can handle by using boundary exchange together with a single area CNN. In this method, a wide predicting area is regarded as overlapping the single network model's prediction area. The prediction is performed for each and repeated until the overlapping portion, which is the boundary, converges. We currently have confirmed that the boundary calculation converges, and we improve the model in the future to improve the accuracy of the prediction.

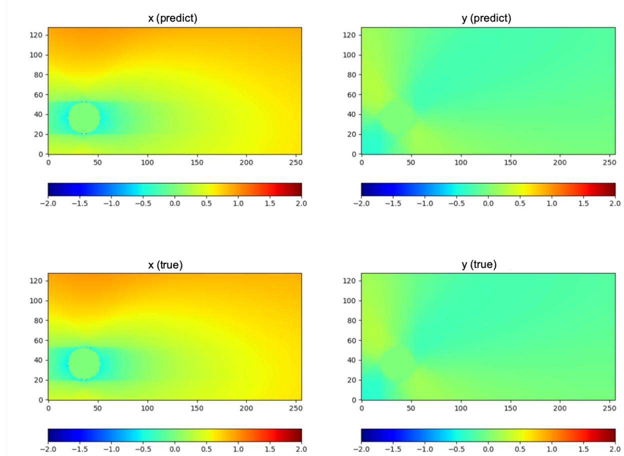

Figure 1: Predicting results. The first column shows the predict of CNN. The second column shows the LBM solution.

In this poster, we provide the method and implementation of steady flow prediction using CNN with boundary exchange and show the predicting results of this method and LBM solutions.

REFERENCES

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