Reducing the Spatial Discretization Error in Coarse CFD Simulations Employing Deep Learning

Authors:

- Jesus Gonzalez-Sieiro, Basque Center for Applied Mathematics, University of Basque Country (UPV/EHU) (jgonzalez@bcamath.org)
- David Pardo, University of Basque Country (UPV/EHU), Basque Center for Applied Mathematics (dzubiaur@gmail.com)
- Vincenzo Nava, Basque Center for Applied Mathematics, TECNALIA (vnava@bacmath.org)
- Victor M. Calo, Curtin University (vmcalo@gmail.com)
- Markus Towara, Aachen University (towara@stce.rwth-aachen.de)

Abstract: Many Computational Fluid Dynamics (CFD) applications that employ the Finite Volume Method (FVM) require fine spatial discretisations, which are often computationally prohibitive. In these cases, Deep Learning (DL) has emerged as a key technology to enhance traditional algorithms. In this work, we reduce the spatial discretisation error on coarse meshes by learning from fine-mesh data, following a super-resolution approach. Specifically, we embedded a feed-forward neural network in the workflow of a traditional FVM solver to interpolate face velocities from cell centre values. Thus, we obtain a solver-in-the-loop [1] model, whose physics needs to be differentiable to be correctly trained. For that, we use the open-source CFD code OpenFOAM and its discrete adjoint version [2] for the differentiation process. We also developed a fast communication method between TensorFlow (Python) and OpenFOAM (c++) to speed up the training process. We applied the model to the flow past a square cylinder problem, reducing the error to about 50% for simulations outside the training distribution compared to the traditional solver in the x- and y-velocity components using an 8x coarser mesh. The training is affordable in terms of time and data samples since the architecture exploits the local features of the physics while generating stable predictions for mid-term simulations.

References:

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