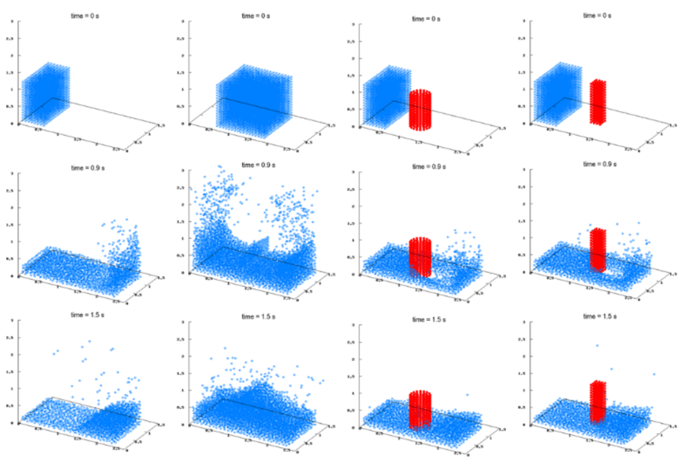
Towards real-time fluid dynamics simulation: A Data-driven NN-MPS method

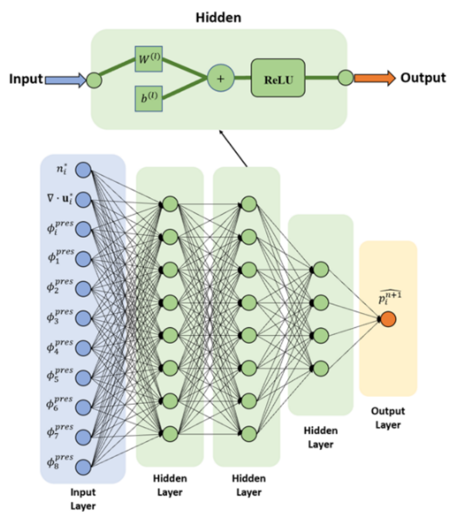
Zijie Li[1], Zichao Jiang[1], Zijun He[1], Qinghe Yao[1]

[1]School of Aeronautics and Astronautics, Sun Yat-sen Uniersity, China

Abstract

As a mesh free Lagrangian particle method, the Moving Particle Semi-implicit (MPS) method [1] has been proven effective in many engineering problems. The implicit pressure calculation mode in MPS brings robustness but also makes it computationally expensive. Developing data-driven models is a common way to reduce the computational cost in physics problem, but many of the traditional data-driven models suffered from limited application scalability for simple regression algorithms they employed are not “deep” enough to capture the encoding behind physics problems. Recent progress on computing power opens up the possibility for the implementation of more advanced and efficient data-driven models. For computational fluid dynamic problem, machine learning techniques like random forest [2] and convolutional neural network [3] are implemented to improve the computing performance of numerical simulation. In this work, we combine the physic intuition from MPS with machine learning algorithm to construct a data-driven model in order to address the computing performance problem of MPS. A fully connected artificial Neural Network (NN) is employed to replace the traditional iterative solver of pressure Poisson equation (i.e. PCG, CG method). We reformulated the pressure Poisson equation as a regression problem and designed context-based feature vectors for particle based on pressure Poisson equation. The trained NN maintains the accurate and stable characteristic of original MPS while drastically speeding up the pressure calculation step. Furthermore, neural network does not require any iteration and is able to calculate the pressure of each particle in an element-wise mode, making it very suitable for parallelization on multi-core CPU or GPU.





[1] S. Koshizuka, Y. Oka, Moving-Particle Semi-Implicit Method for Fragmentation of Incompressible Fluid, Nucl. Sci. Eng. 123 (1996) 421–434. doi:10.13182/NSE96-A24205.

[2] L. Ladicky, S. Jeong, B. Solenthaler, M. Pollefeys, M.H. Gross, Data-driven fluid simulations using regression forests, ACM Trans. Graph. 34 (2015) 199:1-199:9.

[3] J. Tompson, K. Schlachter, P. Sprechmann, K. Perlin, Accelerating Eulerian Fluid Simulation With Convolutional Networks, CoRR. abs/1607.03597 (2016). http://arxiv.org/abs/1607.03597.