Accelerating Lattice Boltzmann Methods using a deep learning approach

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Artificial Intelligence (AI) recently emerges in the engineering fields as a new approach to handle complex systems and elaborate physical models. *Deep learning* is one of those methods, based on a training/validation technique, which has shown outstanding results. For instance, a Go virtual player (one of the most difficult problem in AI) has been recently trained using a deep learning strategy, and has won for the first time a world-class professional in a five-game match in 2016.

In fluid mechanics, breakthrough in numerical methods can be expected by using such a technique to develop complex physical models or enhance current numerical solvers [1]. This project will focus on the Lattice Boltzmann Method (LBM) which was revealed as an effective solver to compute low-Mach number flows because of its high-accuracy and low-cost advection scheme. Compared with Navier-Stokes solvers, the equations to be solved in LBM are discretized in time, space, and velocity, the latter requiring a specific model known as *lattice* where a few discrete velocities are chosen among the continuous velocity space. Such a method yields effective computation with outstanding accuracy at low Mach numbers. However, the accuracy and numerical costs of the LBM for higher Mach numbers ($M > 0.3$) is still a challenge, which requires new developments.

Therefore, this project intends to improve current LBM methods using a deep learning strategy. This internship will focus on the classical weakly compressible 2D formulation available in the code Palabos, where the velocity space is discretized with a standard *lattice* 2DQ9, i.e. where 9 discrete velocities are used. Note that the more velocities are computed, the more expansive and more accurate the simulation is. The main question addressed in this internship is: can we compute less velocities while keeping the same level of accuracy? One key idea is to use deep learning to learn how to compensate the reduced number of velocities, for example through learnt source terms or learnt extra discrete velocities.

This internship for LBM on weakly compressible flows will be a first step towards the improvement of LBM methods at high Mach number flows, where a reduced number of velocities at constant accuracy might lead to significant breakthough.

Pre-requist : a high motivation for new challenges and innovative approaches, a strong background in machine learning and/or in fluid mechanics. Knowledge about C++ and the linux environment would be most appreciated.

[1] J. Thompson, K. Schlachter, P. Sprechmann and K. Perlin, Accelerating Eulerien Fluid Simulation With Convolutional Networks