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Prediction of unsteady flow using physics-informed deep learning methods

Summary

Unsteady flow fields are commonly predicted using numerical flow simulations. Depending on the used method, very accurate solutions can be obtained. Despite the high accuracy, such simulations are often very time-consuming and costly, as the flow fields must be computed for each timestep. Yet, in cases such as controlling the movements of aerial vehicles, fast predictions of multiple future timesteps are required. Deep learning methods could open new and cheaper options to conventional simulations.

It is known that fluid flows present specific flow features. These flow structures can be attributed to certain motions of the flow which hints at the possibility that these spatial features can be learned by neural networks. Typically, neural networks are trained in a way that the difference between generated and ground truth images, the loss, is minimized. This thesis investigates, among others the possibility of improving the training and accuracy of neural networks by including physics based on the governing equations. For this purpose, predictions of two-dimensional unsteady flow fields around a cylinder using physics-informed deep learning methods are studied at different Reynolds numbers.

A Generative Adversarial Network is trained to predict the next time step of time sequence using data obtained by numerical simulations. The performance of the network is then assessed by evaluating the predictions of flow fields that were not part of the networks training. Physical laws are included during the training through a modification of the loss functions by addition of a supplementary term based on the Lattice-Boltzmann equation. Two different physical losses were proposed and tested. The first version uses finite differences to discretize the Boltzmann equation. The second version is based on the time discretized form of the Boltzmann equation with the BGK model approximation that is solved in a two-step fashion.

In all three cases, without, with physical loss 1 and with physical loss 2 good result were obtained. The first physical loss showed a great stabilizing potential, although at the cost of a slightly higher average error. For the second physical loss the stabilization effect was less visible, however, a faster error convergence was observed, especially in the initial phase of the training. A parameter study has shown that the use of a smaller weighting factor for the first physical loss can reduce the average error further while still stabilizing the training process.

The first results have shown that physical losses can potentially stabilize and improve the predictions of unsteady flow fields by neural networks. Based on the implemented network structure, further investigations are foreseen to evaluate the influence of physical losses for more complex flow problems.