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Parametrized Flow Predictions using Physics Informed Neural Networks

S. Wassing[1*], S. Langer[*], P. Bekemeyer[*]

[*] German Aerospace Center (DLR), Institute for Aerodynamics and Flow Technology, Lilienthalplatz 7, 38108 Braunschweig, Germany
[1] simon.wassing@dlr.de

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The motion of fluids gives rise to nonlinear partial differential equations (PDEs) such as the Euler and Navier-Stokes equations. The numerical solution of these equations is e.g. crucial for the design of future aircraft configurations. Therefore, well established computer codes are widely used tools within industrial design processes. These solvers employ a spatial and temporal discretization and calculate solutions with iterative algorithms. Despite a non-negligible progress in efficiency in recent years, long term prospects for further acceleration of these codes seem limited. Especially, transferring these methods to potentially advantageous hardware like graphic processing units has shown to be challenging. Hence, our interest is to investigate numerical methods based on machine learning and deep neural networks to solve Euler and Navier-Stokes equations.

Recently, methods from deep learning have been successfully employed for solving PDEs by incorporating the differential equations into the loss function that is minimized during the training of a neural network. This approach yields a so-called physics-informed neural network (PINN) [1]. PINNs do not rely on discretizations and can address parameterized problems in a straightforward manner. Therefore, they avoid characteristic difficulties which arise when using traditional first-principle based solvers. This has raised the question, whether PINNs may be a viable alternative to conventional methods in computational fluid dynamics.

Here, we show how PINNs can be used to directly solve the two-dimensional Euler equations for parametrized geometries. With this approach a single network is obtained that yields flow solutions in a continuous parameter space. In comparison, traditional methods require seperate solver evaluations for every parameter set. The workflow combines various techniques to facilitate the PINN training. The solution accuracy and computational cost are compared to established methods. The presented results showcase the potential applicability and also limitations of PINNs for realistic tasks like design optimization which conventionally call for a high number of solver evaluations.

REFERENCES

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