

Data-driven turbulence modeling with JAX-SPH

Semester Thesis/Master's Thesis

The emergence of powerful automatic differentiation (AD) libraries like [TensorFlow](#), [PyTorch](#), and [JAX](#) has motivated the development of differentiable computational fluid dynamics (CFD) frameworks (e.g., [JAX-CFD](#), [PhiFlow](#), [JAX-Fluids](#)). In scientific machine learning (ML), AD allows the discovery of novel physical and numerical models by propagating gradient information through entire numerical algorithms, i.e., ML models can be optimized *end-to-end*.

Smoothed Particle Hydrodynamics (SPH) is a Lagrangian discretization scheme for the compressible and incompressible Navier-Stokes equations ([Morris et al. 1997](#)). Although being originally devised for applications in astrophysics, SPH has gained traction in recent years as a versatile framework for simulating complex physics. Given the need for a differentiable SPH code, we have developed a high-fidelity SPH framework based on the differentiable particle simulator [JAX-MD](#). Following this naming convention of JAX-derived codes, our AD framework is entitled JAX-SPH.

Despite the increasing popularity of SPH, turbulence modeling in SPH is not as explored as compared to mesh-based methods. However, certain SPH discretizations function as implicit subgrid-scale (SGS) models ([Adami et al. 2012](#)) and SPH exhibits statistics of turbulent flows ([Ellero et al. 2010](#) and [Borreguero et al. 2019](#)). In this work, we want to make use of the AD capabilities of JAX-SPH and learn explicit SGS closure models for turbulent flows. Considering canonical turbulent flows, we want to explore how turbulent dynamics can be captured by data-driven methods. Especially, we are interested in what network architectures are suitable to model unresolved turbulent motions in SPH.

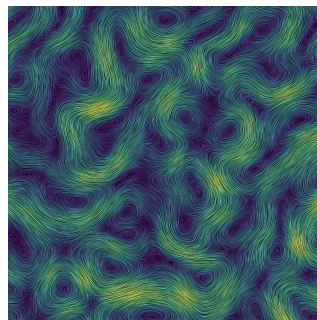


Figure 1: Two-dimensional decaying turbulence with $Re = \infty$ generated with the JAX-SPH CFD code.

Tasks

- Familiarize yourself with the JAX-SPH code.
- Conduct simulations of canonical turbulent flows.
- Implement and train neural networks for data-driven SGS modeling.

Requirements

- Programming experience in Python.
- Interest in computational fluid dynamics/numerical solution of partial differential equations.
- Beneficial: Gas Dynamics, Applied CFD, Turbulent Flows, Numerical Methods for Conservation Laws.

Contact

Fabian Fritz (fabian.fritz@tum.de) and Deniz Bezgin (deniz.bezgin@tum.de).