Karlsruhe Institute of Technology

Autonome Lernende Roboter (ALR) and Institut für Fahrzeugsystemtechnik (FAST)

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Project Type

- ☑ Master Thesis
- ☑ Bachelor Thesis
- ☑ Research Project

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Difficulty

Algorithmic

Math

Application

Differentiable FEM for Advanced Material and Process Optimization

Description

This thesis explores inverse design and optimization for advanced manufacturing using JAX-FEM, a differentiable finite element solver [2]. While differentiable simulators like PhiFlow have advanced fluid dynamics [1], similar progress for solid mechanics and manufacturing remains limited. Yet, many industrial processes—such as stamp forming, machining, or material optimization—rely on mechanical simulations that are often computationally expensive and difficult to optimize. JAX-FEM fills this gap by providing GPU-accelerated forward simulations with native support for automatic differentiation. This unlocks the possibility to integrate powerful machine learning (ML) methods, such as gradient-based optimization and generative models, directly into the simulation pipeline. The goal is to build a machine-learning-friendly FEM pipeline for tasks like shape and process optimization. Inspired by ML-driven work in textile forming [3], this project will develop standardized inverse tasks to support the design of new materials, automate parameter tuning, and accelerate the development of industrial processes. The resulting framework will help reduce manual engineering efforts and enable fast iterations with fewer simulations.

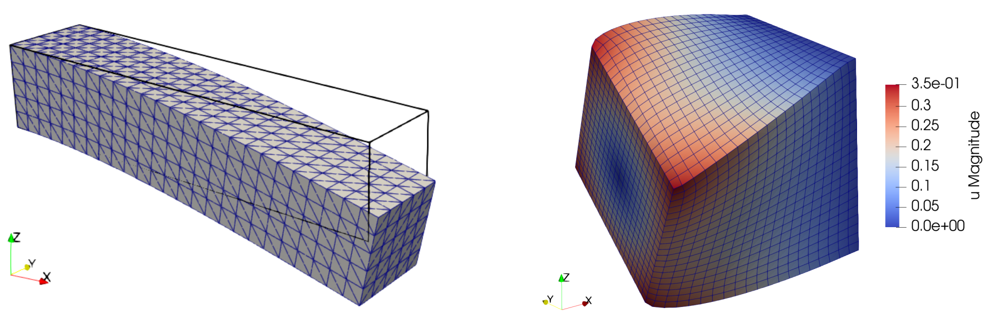

Figure 1: Examples of different elasticity models from [2].

Tasks

- Explore JAX and JAX-FEM and try out their examples.
- Create a simple planar bending task.
- Integrate simple ML techniques (e.g. gradients-based optimizations, or generative modeling via diffusion models).
- Try out with variable geometry and conduct an analysis of the approaches.

References

[1] Philipp Holl and Nils Thuerey. Φ_{flow} (PhiFlow): Differentiable simulations for pytorch, tensorflow and jax. In *International Conference on Machine Learning*. PMLR, 2024.

[2] Tianju Xue, Shuheng Liao, Zhengtao Gan, Chanwook Park, Xiaoyu Xie, Wing Kam Liu, and Jian Cao. Jax-fem: A differentiable gpu-accelerated 3d finite element solver for automatic inverse design and mechanistic data science. *Computer Physics Communications*, 291:108802, 2023.

[3] Clemens Zimmerling. *Machine Learning Algorithms for Efficient Process Optimization of Variable Geometries at the Example of Fabric Forming*. PhD thesis, Karlsruhe Institute of Technology (KIT), 2022.