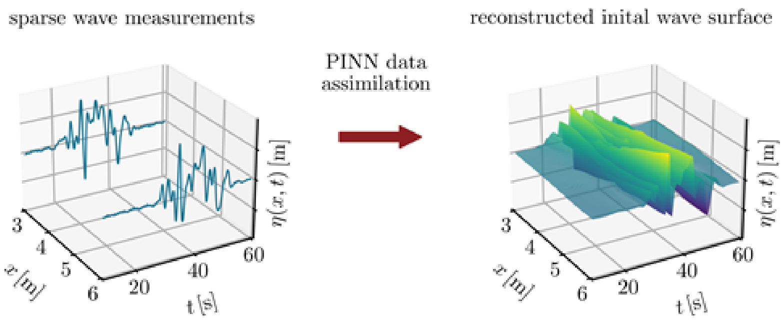
Master Thesis:
Speed-Up Training of Physics-Informed Neural Networks

Ocean engineering activities benefit from real-time predictions of ocean wave conditions a few minutes in advance. Most numerical and machine-learning-based wave prediction methods presuppose immediate access to initial wave data. However, as ocean waves are often measured by buoys, sparsely positioned in space, first a reconstruction of high-resolution spatio-temporal wave surfaces (known as data assimilation) is imperative to initialize the subsequent wave forecast.



For this data assimilation task, we have developed a novel method based on physics-informed neural networks (PINNs)[1]. The idea of this approach is to parameterize the physical equations governing the wave elevation $\eta(x,t)$ as a neural network. While our PINN approach already yields good reconstruction accuracy, currently significant computational time is required for the assimilation due to the necessity of retraining the PINN for each new wave measurement. This makes the real-time capability of the entire prediction process (consisting of PINN-assimilation and a subsequent forecast) impossible so far. For this reason, this thesis is intended to investigate the possibility of accelerating PINN training for wave data assimilation.

The scope of this work covers the following tasks:

- Familiarization with PINNs in general and the basic principles of the physics of water waves
- Literature review on state-of-the-art methods for the acceleration of PINN training
- Implementation of selected methods
- Evaluation by comparison of computational efficiency and reconstruction accuracy

Prerequisites:

- Experience and strong interest in programming, preferably with Python (PyTorch)
- Interest in advanced machine learning techniques
- Independent way of working, curiosity and communication skills

The thesis can be written in German or English.

[1] M. Raissi, P. Perdikaris, G.E. Karniadakis: Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, 2019. https://doi.org/10.1016/j.jcp.2018.10.045

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