Physics-informed neural networks for phase-resolved wave data assimilation and prediction

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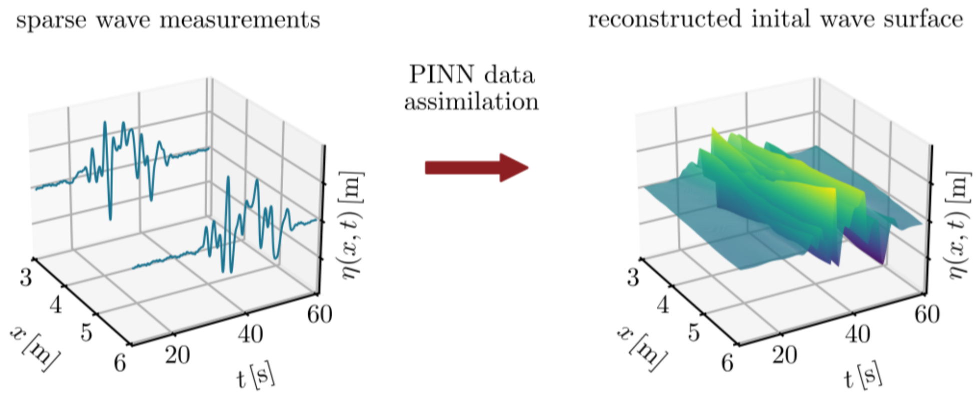
The accuracy of phase-resolved ocean wave prediction methods significantly depends on precise spatio-temporal initial conditions. However, the sparse nature of wave measurements in space or time renders the data assimilation process as highly ill-posed inverse problem. This often presents challenges and requires substantial computational resources when using conventional grid-based numerical solvers.

To address these issues, we explore the application of physics-informed neural networks (PINNs) [1] for wave data assimilation and also subsequent prediction: PINNs integrate observational data with underlying physical laws by parameterizing the solutions of partial differential equations (PDEs) as neural networks. Specifically, we showcase a PINN framework capable of solving the fully nonlinear potential flow equations, enabling the reconstruction of both, wave surfaces $\eta(x,t)$ and the corresponding physically consistent potential field $\Phi(x,t,z)$, from sparse surface buoy measurements $\eta(t)$ only. The PINN trained to assimilate the measurement data can subsequently also be applied to predict the future evolution of the considered wave system.

Our proposed method indicates potential in improving the reliability of wave predictions by combining wave physics given by wave model equations with data driven methods. It thus may contribute to enhancing the safety and efficiency of ocean engineering activities.



[1] M. Raissi, P. Perdikaris, G.E. Karniadakis, 2019. *Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations.* Journal of Computational Physics 384. doi: https://doi.org/10.1016/j.jcp.2018.10.045.