Physics-Informed Neural Networks for System Identification of Fluid-Structure Interactions

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Fluid–structure interaction (FSI) problems are characterized by the interdependence of thefluid motion and structural response. Advances in computing speed and storage capacity have enabled the development and implementation of high-fidelity algorithms and simulations that capturesignificant physical features of complex FSI problems. Still, such simulations may not discern underlying phenomena that are usually interrelatedin a complex manner, which makes it difficult to characterize the relevant causal mechanisms. Besides, extensive computational resources and time associated with the implementation of high-fidelity simulations usually limit the number of configurationsfor design and optimization purposes or effective control strategies.

Physics governing fluid structure interactions are usually represented by nonlinear partial differential equations that can yield complex responses. Additional complexities include memory or future effects. For example, the lift on flapping wing depends on the history of the flapping motion and generated wake. As another example, wave excitation and radiation damping forces on floating or submerged structures are represented by convolution integrals that respectively account for future wave conditions and the motion's history. Such integrals require storage and updating of the history of the motions at every time step, which presents a significant computational burden, especially in problems involving different degrees of freedom or motions. To address these issues, simplifying assumptions are usually made to develop reduced-order models that are capable of characterizing relevant physical phenomena while yielding important response characteristics.

In contrast to computationally expensive brute-force high-fidelity simulations, physics informed neural networks (PINN) canleverage deep neural networks capabilities to infer hidden/latent information of interest from scattered data in time and space. In the presentation, we implement a data-driven system identification (discovery) of different examples of fluid structure interactions. Specifically, data training is performed to identify the coefficients in physics or phenomena-based governing equations of these examples, which include integro-differential equations, as required for specific applications.