Physics-informed neural networks modeling for systems with moving immersed boundaries: application to an unsteady flow past a plunging foil

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Abstract

Recently, physics informed neural networks (PINNs) have been explored extensively for solving various forward and inverse problems and facilitating querying applications in fluid mechanics applications. However, work on PINNs for unsteady flows past moving bodies, such as flapping wings is scarce. Earlier studies mostly relied on transferring to a body attached frame of reference which is restrictive towards handling multiple moving bodies or deforming structures. Hence, in the present work, coupling the benefits of using a fixed Eulerian frame of reference and the capabilities of PINNs, an immersed boundary aware framework has been explored for developing surrogate models for unsteady flows past moving bodies. Specifically, simultaneous pressure recovery and velocity reconstruction from Immersed boundary method (IBM) simulation data has been investigated. While, efficacy of velocity reconstruction has been tested against the fine resolution IBM data, as a step further, the pressure recovered was compared with that of an arbitrary Lagrange Eulerian (ALE) based solver. Under this framework, two PINN variants, (i) a moving-boundary-enabled standard Navier-Stokes based PINN (MB-PINN), and, (ii) a moving-boundary-enabled IBM based PINN (MB-IBM-PINN) have been formulated. Relaxation of physics constraints in both the models is identified to be a useful strategy in improving the predictions. A fluid-solid partitioning of the physics losses in MB-IBM-PINN has been allowed, in order to investigate the effects of solid body points while training. This strategy enables MB-IBM-PINN to match with the performance of MB-PINN under certain loss weighting conditions. Interestingly,