Understanding the training of PINNs for unsteady flow past a plunging foil through the lens of input subdomain level loss function gradients

Rahul Sundar[1*], Didier Lucor[2], and Sunetra Sarkar[1]

[1*]Department of Aerospace Engineering, Indian Institute of Technology Madras, Chennai 600036, India

[2] Laboratoire Interdisciplinaire des Sciences du Numérique LISN-CNRS,

Université Paris-Saclay, Orsay 91403, France

[*]Email: rahulsundar@smail.iitm.ac.in

Abstract

Recently immersed boundary method-inspired physics-informed neural networks (PINNs) including the moving boundary-enabled PINNs (MB-PINNs) have shown the ability to accurately reconstruct velocity and recover pressure as a hidden variable for unsteady flow past moving bodies. Considering flow past a plunging foil, MB-PINNs were trained with global physics loss relaxation and also in conjunction with a physics-based undersampling method, obtaining good accuracy. The purpose of this study was to investigate which input spatial subdomain contributes to the training under the effect of physics loss relaxation and physics-based undersampling. In the context of MB-PINNs training, three spatial zones: the moving body, wake, and outer zones were defined. To quantify which spatial zone drives the training, two novel metrics are computed from the zonal loss component gradient statistics and the proportion of sample points in each zone. Results confirm that the learning indeed depends on the combined effect of the zonal loss component gradients and the proportion of points in each zone. Moreover, the dominant input zones are also the ones that have the strongest solution gradients in some sense.

Keywords: Immersed boundaries, Physics informed neural networks, surrogate modeling, unsteady flows, plunging foil

1 INTRODUCTION

Physics-informed neural networks have become promising for their use in solving complex inverse problems such as hidden physics recovery, data-driven equations discovery, uncertainty quantification, Plain vanilla PINNs ([1] are however difficult to train when the systems exhibit strong spatiotemporal gradients. Hence, recently, authors have proposed different strategies to train PINNs better, such as adaptive sampling, modified architectures, static and dynamic loss weighting.

Surrogate modeling of unsteady flow past moving boundaries such as flapping wings become challenging if the underlying high-fidelity simulation data used for such an endeavour is obtained using the immersed boundary method [2, 3]. This is because, IBM uses a fixed Eulerian background grid for the fluid, whereas the solid boundary is described by a set of Lagrangian markers. At any time instant, there exist eulerian grid cells bounded by the solid boundary which consists of fictitious flow field data.