Commun. Comput. Phys.
doi: 10.4208/cicp.OA-2023-0235

Vol. **36**, No. 4, pp. 1021-1052
October 2024

A Neural Particle Method with Interface Tracking and Adaptive Particle Refinement for Free Surface Flows

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Received 3 September 2023; Accepted (in revised version) 8 January 2024

Abstract. This paper is devoted to a new neural particle method (NPM) based on physics-informed neural networks (PINNs) for modeling free surface flows. Utilizing interface tracking techniques and machine learning (ML) modeling, the new NPM approach with interface tracking and adaptive particle refinement (NPM-LA) is suggested. This method encompasses properties of tracking the interface particles and ensuring the preservation of the designated distribution pattern for interior fluid (computational) particles. The determination of the corresponding physical quantities at these particles is accomplished through the process of inference, a distinctive feature facilitated by ML. The proposed NPM-LA effectively provides solutions for both appropriately tracking the morphology of complex flow surfaces and enhancing the accuracy by dynamically redistributing particles into desired patterns within the computational domain. Two testing cases (the 2D Poiseuille flow problem and a rotating square patch of inviscid fluid) are adopted to examine the performance of the proposed NPM-LA method. The applications to experiments of dam break and wave breaking problems are explored for demonstrating the capability of capturing the complex deforming flow surface.

AMS subject classifications: 35Q30, 35Q31, 68T07, 76D05

Key words: Neural particle method (NPM), Lagrangian approach, adaptive particle refinement, interface tracking, physics-informed neural networks (PINNs).

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1 Introduction

Hydrodynamic simulations play a crucial role in understanding and predicting the behavior of fluids in various domains, including environmental modeling, coastal engineering, and offshore structures. Many practical applications such as flood propagation of dam break and wave breaking [24, 50], mitigation and prevention of tsunami [36], design of offshore wind turbines [4], and control and maneuverability of floating objects in ocean [9], often involve complex flow physics with the needs for precisely tracking motions of free surface, deformable boundaries and moving objects.

Traditional mesh-based numerical methods for hydrodynamic simulations, such as finite difference, finite volume, and finite element methods, which have been fully developed and advanced in the past, often face significant challenges in accurately capturing complex flow physics, handling free surface flows, and efficiently adapting to changing boundary and interfacial conditions. Meshless methods or so-called particle-based methods, on the other hand, have been developed by removing the mesh dependency burden from mesh-based methods. These meshless methods such as the Smoothed Particle Hydrodynamics (SPH), Moving Particle Semi-Implicit (MPS), and Discrete Element methods (DEM) [8, 12, 25] essentially employ a Lagrangian formulation that solve the Navier-Stokes equations by tracking the fluid motion with discrete particles and omitting the convective effects. The SPH is one of the most popular meshless methods that has been widely used in many hydrodynamic applications, including the dam breaking, wave breaking, and fluid-structure interaction problems [44, 49]. However, this type of meshless method still requires to overcome intrinsic disadvantages associated with the lack of connectivity of neighboring particles to address challenging issues including solution convergence, accuracy and model stability, boundary conditions enforcement, as well as the adaptive mesh strategy that allows for a domain discretization with proper particle spacing to be able to solve practical industrial problems [37].

Recently, the Physics-Informed Neural Networks (PINNs) method has emerged as a promising approach for CFD simulations, combining the strengths of deep learning modeling with the governing equations of fluid dynamics and known physical laws. Raissi et al. [39] proposed the PINNs method, which embedded physical equations, boundary and initial conditions as well as ground truth data into an artificial neural network structure through automatic differentiation (AD) to construct loss functions and further minimizing the loss functions to obtain approximated solutions of governing physical equations. By incorporating physical equations and constraints into the training processes, the neural network can achieve favorable accuracy with much less training data while avoiding the need for explicit meshing and discretization schemes. In addition, the PINNs method is also suitable to solve inverse problems, such as extracting physical parameters from predicted and experimental results. With the aid of its powerful computing capability by graphics processing unit (GPU) acceleration and deep learning modeling flexibility, the PINNs approach quickly draws great attentions in the CFD community and has been utilized to solve many fluid mechanics problems [6, 20].