IAF ASTRODYNAMICS SYMPOSIUM (C1)
Interactive Presentations - IAF ASTRODYNAMICS SYMPOSIUM (IPB)

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ADVANCING SOLUTIONS FOR THE THREE-BODY PROBLEM THROUGH PHYSICS-INFORMED NEURAL NETWORKS

Abstract

First formulated by Sir Isaac Newton in his work "*Philosophiæ Naturalis Principia Mathematica*" the concept of the Three-Body Problem was put forth as a study of the motion of the three celestial bodies within the Earth-Sun-Moon system. In a generalized definition, it delves into the prediction of motion for an isolated system composed of three point masses freely interacting under Newton's law of universal attraction. This proves to be analogous to a multitude of interactions between celestial bodies, and thus, the problem finds great applicability within the studies of celestial mechanics. Despite its importance and numerous attempts by renowned physicists to solve it throughout the last three centuries, no general closed-form solutions have been reached due to its inherently chaotic nature for most initial conditions. Current state-of-the-art solutions are based on two approaches, either machine learning-based or numerical high-precision integration. Notwithstanding the amazing breakthroughs of neural networks, these present a significant limitation, which is their ignorance of any prior knowledge of the problem and chaotic systems presented. Thus, in this work, we propose a novel method that utilizes Physics-Informed Neural Networks (PINNs). These deep neural networks are able to incorporate any prior system knowledge expressible as an Ordinary Differential Equation (ODE) into their learning processes as a regularizing agent. Our model was trained on a dataset composed of 10,000 simulations made with recourse to a high-precision n-body integrator. The simulated data belonged to systems with three unitary masses and initial velocity equal to zero, corresponding to a restricted form of the problem. Our findings showcase that PINNs surpass current state-of-the-art machine learning methods with comparable prediction quality and faster inference speed. Despite a slightly better prediction quality, the usability of numerical integrators suffers due to their prohibitively high computational cost. These findings confirm that PINNs are both effective and time-efficient open-form solvers of the Three-Body Problem that capitalize on the extensive knowledge we hold of classical mechanics.