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PHYSICS-INFORMED NEURAL NETWORKS AND THEORY OF FUNCTIONAL CONNECTIONS FOR OPTIMAL SPACE GUIDANCE APPLICATIONS

Abstract

Over the past decade, machine learning in general and deep learning in particular have experiences a huge raising in popularity. The dramatic growth in both available data and computational resources, promoted a transformation in various disciplines (e.g. image recognition, robotics, computer vision) driven by advances in artificial intelligence methods. Recently, within the space flight mechanics community, there has been a marked interested in understanding how machine learning can be effectively applied to solve problems in astrodynamics, including orbit determination, low-thrust guidance and control, pose estimation, just to mention a few. Generally, the use of deep and shallow networks methodologies underlines a data-driven approach where neural networks approximate the unknown functional relationship represented by the available data. However, whenever dealing with space systems dynamics, equations of motion must be always satisfied, i.e. they become linear or non-linear constraints for the problem at hand. In this context, when exploring data-driven machine learning techniques, one of the major questions is how can we ensure that such physical constraints are satisfied. Conversely, the latter also implies the construction of neural approximators that accurately and efficiently solve the ordinary and/or partial differential equations which mathematically represent the fundamental physical principles driving the space system.

In this paper, we demonstrate how to construct a set of neural networks that are trained in a supervised fashion to solve specific tasks typically encountered in astrodynamics and space flight mechanics while satisfying any physical constraint generally represented by a set of differential equations. More specifically, we combine and merge two powerful theoretical constructs, i.e. Theory of Functional Connections (TFC) and Extreme Learning Machines (ELM) Theories, to efficiently, fastly and accurately solve differential equations encountered in typical astrodynamics problems via neural networks. The resulting Physics-Informed Neural Networks (PINN) form a new class of data-efficient neural approximator that naturally encode the physical laws underlying the overall dynamics. We will focus on optimal control problem and we show how we can fastly and effectively use single-layer forward networks with boundary conditions analytically satisfied by the TFC-derived constrained expressions to solve energy-optimal guidance problems in both relative motion and circular restricted three-body dynamics.