Aerospace Europe Conference 2023
Joint 10th EUCASS – 9th CEAS Conference

Abstract #XXX *(to be filled by the organizers)*
Preferred Topics: FDGNCAV

Corresponding author: CUEVAS DEL VALLE, Sergio
e-mail of corresponding author: s.cuevas.2017@alumnos.urjc.es

Type: Oral
Status of corresponding author: Student
For student corresponding author:

Title

Embedding Pontryagin's Principle in Neural Networks for Optimal Asteroid Landing

Authors

Sergio Cuevas del Valle[1], Pablo Solano-López[2], Hodei Urrutxua [3]*

** Corresponding author*
[1] Aerospace Systems and Transport Research Group, Universidad Rey Juan Carlos, 28942 Fuenlabrada, Spain, *s.cuevas.2017@alumnos.urjc.es*
[2] Aerospace Systems and Transport Research Group, Universidad Rey Juan Carlos, 28942 Fuenlabrada, Spain, *pablo.solano@urjc.es*
[3] Aerospace Systems and Transport Research Group, Universidad Rey Juan Carlos, 28942 Fuenlabrada, Spain, *hodei.urrutxua@urjc.es*

Abstract

The advent of Machine Learning (ML) and its applications at engineering in general and to space engineering in particular, has allowed to rethink complex problems in space dynamics, ranging from learning dynamical models from telemetry to spacecraft operations and decision taking in general.
It is more and more common to find such techniques as helping tools for the design of general guidance, navigation, and control systems. As an interesting example, ML techniques have been applied as solvers of complex optimal control problems, such as rendezvous between orbital objects or landing in partially unknown environments. In short, Neural Networks (NN) models can be constructed to learn these optimal solutions and then generalize them to new problems of similar statement.
Optimal control problems are natural and intrinsically valuable to astrodynamics and general mission design, in which tight performance constraints exist. Despite the vast literature on the topic, Optimal Control Theory still poses open/untackled problems, especially with regards to real time performance onboard legacy systems [1]. The design of these optimal control laws is constrained by the need to solve complex nonlinear programming problems associated to a Hamiltonian Minimization Condition (HMC), either in the form of Pontryagin's Maximum Principle or the complementary Hamilton-Jacobi-Bellman PDE equation. This is true for both the so-called direct and indirect approaches, in which discretization is leveraged to solve the primal or dual optimal problem, respectively. The direct approach is easier to solve but suffers from the curse of dimensionality; the indirect method provides a rigorous way to verify optimality but is subject to intrinsic instability arising from its symplectic structure. In both cases computational capabilities are required to solve the associated nonlinear programming optimization, which may not always be available. In this sense, NNs offer an alternative to find the same solutions, constructed upon memory storage and not online performance.
Based on recent advances in the field [2,3], this work proposes novel Neural Network training algorithms and architectures to solve with low-cost general Optimal Control problems. In particular, the Hamiltonian structure of Optimal Control (given by the application of Pontryagin's Maximum Principle) is leveraged to modify physics-informed NN [4] to the control practitioner's advantage. This HMC embedding is used to construct and train the network in a robust and generalizable manner. The training algorithm is designed to output initial guesses for the problem's boundary values while capturing the associated transversality conditions and the state/co-state dynamics. In this way,

with low computational effort once the network is trained, the major difficulty in the Optimal Control indirect approach is removed, immediately making available the optimal state-control pair.

The proposed architectures and algorithms are then applied to classical optimal control problems, including time and fuel stochastic optimal landing on an oblate asteroid of a binary system. After presenting and validating the dataset generation procedure, several NN schemes are benchmarked with test cases to check the boundaries of their application. Finally, further advances and open lines of research are discussed and conclusions presented.

References

[1] Ross, I. & Karpenko, Mark. (2012). A review of pseudospectral optimal control: From theory to flight. Annual Reviews in Control. 36. 182–197. 10.1016/j.arcontrol.2012.09.002.

[2] Solano-López, P. & Barea Vilar, A. & Gutiérrez-Ramón, R. & Urrutxua Cereijo, H. (2022). Assessment of Machine Learning Techniques for Time-Optimal Landing Trajectories. 9TH European Conference for Aeronautics and Space Sciences (EUCASS), 10.13009/EUCASS2022-4761.

[3] Meng, T., Zhang, Z., Darbon, J., & Karniadakis, G. (2022). SympOCnet: Solving Optimal Control Problems with Applications to High-Dimensional Multiagent Path Planning Problems. SIAM Journal on Scientific Computing, 44(6), B1341-B1368.

[4] M. Raissi, P. Perdikaris, G.E. Karniadakis (2019), Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, Journal of Computational Physics, 378, 686-707, 10.1016/j.jcp.2018.10.045.