Internship in ESA's Advanced Concepts Team
On
Backward generation of Optimal Samples for Space Dynamics

European Space Research and Technology Centre
ESA ESTEC

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Topic description

The construction of large databases of optimal trajectories is at the core of recently developed advanced techniques in aerospace systems [1-4]. Such databases are typically used for the purpose of training and informing AI systems (e.g. reinforcement learning or supervised/imitation learning based system). One drawback of these pioneering techniaues is that the database construction can be a lengthy task full of numerical pitfalls.

Scientists at the Advanced Concepts Team have recently developed a new methodology, called the backward generation of optimal samples [6], able to create optimal trajectories using Pontryagin's Maximum principle [5], but without having to solve a two-point-boundary-value problem (TPBVP) and thus without incurring in all the numerical and computational limitations of associated numerical methods. The method was tried on an Earth-Venus transfer where equinoctial parameters were used to represent the spacecraft state, but it is generic and applicable to any dynamical system.

The main objective of this internship is to implement and study such a method on further dynamical systems, thus enlarging the portfolio of success cases to rendezvous dynamics, quadcopter dynamics, rocket descent dynamics etc.

Candidate's tasks

- Understand the backward generation of optimal samples technique.
- Propose a number of dynamical systems and optimal control problem where it would make sense to test the technique.
- Implement Pontryagin's equations for the agreed systems and the backward generation of optimal samples
- Generate and study the resulting databases of optimal trajectories.

The ideal candidate

Mandatory:

- Strong programming skills in Python.

- Experience with optimal control theory and indirect methods (and their implementation).
- Understanding of supervised learning and reinforcement learning.

References

[1] Sánchez-Sánchez C, Izzo D. Real-time optimal control via Deep Neural Networks: study on landing problems. Journal of Guidance, Control, and Dynamics. 2018 May;41(5):1122-35.

[2] Li S, Ozturk E, De Wagter C, de Croon GC, Izzo D. Aggressive online control of a quadrotor via deep network representations of optimality principles. arXiv preprint arXiv:1912.07067. 2019 Dec 15.

[3] Li H, Topputo F, Baoyin H. Autonomous Time-Optimal Many-Revolution Orbit Raising for Electric Propulsion GEO Satellites via Neural Networks. arXiv preprint arXiv:1909.08768. 2019 Sep 19.

[4] Cheng L, Wang Z, Jiang F, Zhou C. Real-time optimal control for spacecraft orbit transfer via multiscale deep neural networks. IEEE Transactions on Aerospace and Electronic Systems. 2018 Dec 24;55(5):2436-50.

[5] Izzo, D. and Öztürk, E., 2020. Real-Time Optimal Guidance and Control for Interplanetary Transfers Using Deep Networks. arXiv preprint arXiv:2002.09063.

[6] Pontryagin, L.S., 2018. Mathematical theory of optimal processes. Routledge.