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ORBITAL ANOMALY RECONSTRUCTION USING DEEP SYMBOLIC REGRESSION

Abstract

This work explores the application of Deep Learning-based Symbolic Regression for the autonomous reconstruction of orbital anomalies. Orbital anomalies are detectable deviations from the state of an object that can be predicted from the propagation of some observable initial conditions. We contemplate anomalies that can derive from unmodelled natural phenomena or from intentional and unintentional orbital manoeuvres. An accurate modelling of atmospheric density fluctuations, for example, allows informing the space weather.

Leveraging the modelling capacity of recurrent neural networks and the sparse representability of dynamical systems in orbital mechanics (i.e., only a small set, in the space of all possible functions, has a physical meaning), the proposed approach allows one to generate a symbolic representation of orbital anomalies from state observations. In other words, we use sparse measurements of position and velocity, with associated uncertainty, to derive a symbolic representation of the unmodelled part of the dynamics that can explain the deviations from the propagated states.

The advantage of such an approach, compared to more traditional filtering techniques, is twofold: it provides an explicit analytical representation of the phenomenon causing the anomaly and it provides a better long term prediction of the dynamics of the object under consideration. The use of Deep Learning-based Symbolic Regression outdoes more traditional Genetic Programming-based approaches in that it is less prone to overfitting and can easily incorporate constraints.

The explicit dependence, with respect to time, of the symbolic representation, permits to indirectly model the evolution of unobservable states, whose behaviour can be later inferred from the analysis of the solution itself. The proposed approach yields solutions that are robust against measurement noise: its estimation is integrated into the derivation of the missing part of the dynamics.

The performance of the Deep Symbolic Regression will be assessed, using both real (radar and optical-based) and simulated measurements of Low Earth Orbit objects.