ANNEX B. STUDY DESCRIPTION

Hybrid Propagation

Study Reference Number: 16-4101
Type of activity: Standard study (30k€)

Project Summary

Objective

This project will investigate the possibility of machine learning or time series data mining techniques to predict the error of analytical orbit propagators given previous observations.

Target university partner competences

Machine learning, time series data mining, analytical orbit propagation

ACT provided competences

Astrodynamics, machine learning, observational data

Keywords

Machine learning, neural network, time series, data mining, gradient boosting machine, Cartesian genetic programming, hybrid propagation

Study Objective

This study aims to fit a model for the error of analytical orbit propagation methods using machine learning and time series data mining techniques applied to previous observations. The fitness of the resulting model for predicting the error of the analytical orbit propagator is then analysed.

Background and Study Motivation

Orbit propagation of satellites particularly around the Earth plays an important role in managing the space environment. Modern propagation models take into account perturbations due to the Earth's oblateness, aerodynamic drag, and third body perturbations from the Sun and the Moon. While some of these, such as the Earth's oblateness, are well understood and measured, other effects are difficult to model accurately. In particular, the aerodynamic drag is a challenging problem, as it depends both on a constantly changing environment (atmospheric density) as well as the attitude and shape of the satellite. This leads to large errors in situations where the dynamics are dominated by those effects.

High fidelity models including precise models of all these factors are computationally intensive as they require numerical integration with small integrator step sizes to achieve the required accuracy. An analytical solution to the problem is in general not possible as the equations of motion are not integrable. Simplified models of the perturbing forces allow analytical solutions to the orbit propagation to be derived. These solutions, while not as accurate as high-fidelity models, allow very fast propagation, which is often considered sufficient for short time-frames of a few days.

Through the public NORAD catalog as well as ESA's own data, observations of spacecraft states over time are available. Current propagation models either only take the last known observation as the initial state, or use simple models to extract constant parameters (such as the drag coefficient) from it [1]. However, it seems that better use can be made of this detailed trove of data using modern data mining techniques such as time series modelling [2] to improve the accuracy and efficiency of current orbit propagators.

Recently, new approaches have been proposed to improve the accuracy of analytical orbit propagators while maintaining their performance by including the available history of observations. A hybrid propagator [3] is such a method. It represents the trajectory as the sum of an analytical model (such as classical SGP4) and an error function representing the difference between the actual orbit and the analytical model. The error model is fitted using historical observation data. In the method proposed in [3], an individual error function is fitted for each resident space object.

The objective of this study is to use more advanced techniques for hybrid propagators to make these much more useful. In particular, two topics shall be addressed. First, the effect of modelling the error function in different ways. Second, the possibility of a single universal error function to represent the propagator error for different objects shall be investigated.

Models to represent the error include both a model-free approach based on machine learning as well as a heuristic model of the error. The model-free approach learns the shape of the error using some machine learning techniques [4,5], while the heuristic model uses classical time-series prediction methods such as Holt-Winter exponential averaging [6] to express the error function.

The accuracy and effectiveness of each error model implementation will be evaluated in several different relevant orbital regimes for orbit propagation times between 1 and 60 days. The results will be compared to a high-fidelity numerical model as well as actual observations. Test cases will include a variety of objects covering different sizes as well as inclinations and orbital regimes. To ensure the availability of high accuracy tracking data the selected objects must be tracked using laser retro reflectors [7]. The following is a list of orbital regimes of interest and possible objects to be used as test cases:

- LEO: satellites, cube-sats, debris;
  For example Swarm A (lower LEO) and Sentinel 1A (upper LEO)
- MEO: satellites, cube-sats;

For example Galileo

- HEO/GTO: satellites, rocket bodies;
  For example XMM and INTEGRAL
- GEO: satellites, debris.

It seems unlikely that a single universal error function is capable of representing the analytical error for all types of objects in all orbital regimes. The study will thus address the feasibility of an error function capable of representing all objects in a certain orbital regime (LEO, GTO, ...), or all objects belonging to a certain class (upper stages, cube sats, ...). Such generalized error functions would already greatly enhance the practical importance of the method. An interesting side effect could be the possibility of characterizing the observation network used to make the observations being learned.

Proposed Methodology

The following study logic is proposed, though universities are free to propose different approaches if these would better achieve the study objectives:

1. Selection of at least one analytical propagator to study (e.g. SGP4) and a numerical high-fidelity propagator to use as reference;
2. Identification of at least five representative examples of resident space objects covering a range of different orbital regimes and object types;
3. Definition, trade-off and selection of error models to be studied;
4. Development of the required algorithms to train/fit each of the selected error models using both real observation data as well as data generated using the high-fidelity model for a single object;
5. Analysis of the accuracy and computational efficiency of the generated error models for the training objects;
6. Generalization of the error function to classes of similar orbital regimes and objects;
7. Analysis of the accuracy and computational efficiency of the resulting error models for the selected class of objects or orbital regimes;

In particular, the early phase of the study is expected to be performed in close collaboration with the agency. The error models studied will include at least:

- one heuristic time series model,
- one model-free machine learning based approach.

The trade-off for the selection of a machine learning technique will consider at least the following:

- Cartesian Genetic Programming (CGP), [4]
- Neural networks (NN),

- Gradient boosting machines (GBM). [5]

In particular GBM, which has recently garnered substantial interest in the community, seems like a natural candidate to consider for the representation of a generalized error function.

ESA/ACT Contribution

The ACT will contribute in several ways, depending on the needs and expertise:

- Extensive knowledge of machine learning applications, in particular NN and CGP
- Expertise in astrodynamics and orbit propagation
- High quality reference data for measurements of selected resident space objects

Bibliography

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