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ORBIT PREDICTION ACCURACY ANALYSIS USING MONITORED MACHINE LEARNING APPROACH

Abstract

A recently developed monitoring system can automatically maintain the training and evaluating machine learning (ML) models to enhance orbit prediction capabilities on resident space objects (RSOs). The new method leverages accurate state-of-the-art physics models and uses ML methods to provide other necessary details that are unresolved theoretically. Moreover, an information sharing routine based on this system has been proposed. Preliminary results based on TLE catalog have revealed that the monitoring system can indeed maintain the validity of the trained ML models based on some empirical criteria. The results have also exposed several important questions worth further studies, some of which are handled in this paper.

First, the uncertainty propagation of a TLE set is improved particularly for the ML approach. This includes the initial uncertainty estimation of TLE sets as well as the uncertainty propagation using extended Kalman filter (EKF). A common approach to approximate the uncertainty of a TLE set is to use a duration-based polynomial model of the consistency errors of TLE sets falling inside a fixed window, which could fail because the underlying polynomial assumption may not valid. According to our results, such a regression model can generate an either too optimistic or too aggressive extrapolation value for the initial error (where the duration is close to zero). Although this is a minor problem for studies focusing on characterizing the evolution of TLE sets, we need an approach to provide a proper approximation to the initial covariance, which will be developed in this paper.

Second, a fusion strategy to combine the ML-correction with the EKF-prediction is embedded in the new monitoring system. Generally, with a properly tuned fusion strategy, the fused orbit prediction will have both better accuracy and better precision than the EKF-prediction. Even more importantly, the fused prediction uncertainty will be more conservative than directly applying the ML-correction. Since the ML approach is essentially a data-driven modeling technique, it is preferred to trust more on the analytical EKF-predictions, which is adopted in the fusion strategy. With the fusion strategy, new retraining criteria are proposed for the monitoring system, because currently we will always obtain performance metrics which are considered good enough in the old system.

Third, we optimize the program to improve the training and evaluation performance of the system including: 1) the generated training data is cached for reuse in the next re-training period; 2) the re-training of the ML models is carried out for different components of the orbit prediction error concurrently; and 3) the code is compiled to improve the computational efficiency.

In the final paper, the advanced monitoring system will be tested using the same RSOs as the earlier studies and using additional RSOs. We will focus on analyzing the performance and interpreting the underlying causes. The results in this paper will not only serve as another validation of the ML approach, but also make it possible to categorize the RSOs into different groups based on their performance under the monitored ML approach. Furthermore, the generalization capability among similar RSOs in the TLE catalog will be reliably examined for the first time.