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BUILDING AND VERIFYING END-TO-END DEEP LEARNING ENGINES TO DETECT ANOMALIES IN SPACECRAFT TELEMETRY USING SATELLITE DIGITAL TWINS

Abstract

Detecting anomalies in telemetry data captured onboard satellites is a pivotal step toward their safe operation and allows us to respond to failures and hazards quicker. In point anomalies, telemetry values fall outside the nominal range, collective anomalies refer to the telemetry sequences that are anomalous, whereas in contextual anomalies, the values are anomalous within their neighborhood. The out-of-limit detectors in use today can spot point anomalies, and various expert systems have been proposed to cover other events. Although there are machine learning algorithms for detecting anomalous telemetry events, they are heavily parameterized, and the incorrect hyperparameters deteriorate their performance. Thus, thorough verification of the event detection techniques is of paramount importance, especially given that the benchmarks that exist in the literature can be flawed and cannot be used for their unbiased verification which can lead to over-optimistic conclusions. In this paper, we tackle the above-mentioned issues and present our two-step anomaly detection framework, called the Antelope. It exploits deep learning (long short-term memory networks) for predicting the future telemetry values based on the historical data in the first step. Here, we can benefit from either one-to-one or many-to-one strategies, where a telemetry channel can be predicted using historical values of a single or many channels. Then, we confront the predicted values with the actual telemetry, and – if the difference is sufficiently large – we annotate the signal as anomalous. We present our approach toward training and verifying such techniques using benchmark and simulated data. In the latter case, we exploit a simulator developed for the MOVE-II satellite, and show how to effectively train the deep learning models over the nominal data, and how to utilize the simulated anomalies (solar panel or magnetometer failures) to objectively verify the detectors. Over MOVE-II's in-orbit life of over three years, the simulator has been continuously improved and correlated with flight data to closely resemble the current state of the mission. We believe that this approach in which we build the satellite's digital twin in order to synthesize nominal and anomalous data that strictly follows the expected on-board data characteristics to train and validate the detection engines is a viable approach

since real ground-truth data does not exist. Further, it can build more trust in data-driven approaches, as it allows us to start generating simulated data before launching the satellite and verify the anomaly detection algorithms on-ground before deploying them to the spacecraft.