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DATA-DRIVEN FDI FOCUSING ON THE ATTITUDE DYNAMICS OF SPACECRAFT

Abstract

In this study, we develop a way to improve the data-driven FDI (Fault Detection and Isolation) system of spacecraft using the analytical model of attitude dynamics. FDI is recognized as an instrumental element of spacecraft systems. In spacecraft, more than 30% of failures are due to AOCS (Attitude and Orbit Control System), and the autonomous FDI of this subsystem will lead to the success of deep space missions and the operation of multiple satellites with increasing telemetry data. Data-driven FDI is attracting attention due to improvements in computation and available data. Usually, in this method, sensor outputs are evaluated using statistical methods such as machine learning. Challenges of FDI on spacecraft are false detection and oversight of faults in an actual environment. In the case of data-driven FDI for attitude subsystems, it is assumed that the attitude motion is dominant in sensor outputs and fault signals are difficult to notice. For this issue, the concept of model-based FDI can be applicable in that an analytical model of attitude dynamics is utilized to expect sensor outputs and compared them to actual values. By subtracting the changes due to attitude motion from the sensor outputs, residuals are genera. In the residuals, the changes due to faults are made apparent. The nature of the time series of sensor outputs such as mean, autocorrelation, and cross-correlation, strongly express the influence of attitude motion. On the other hand, the nature of the time series of residuals strongly indicates the effect of fault. Unlike that of sensor outputs, it does not depend on the initial value and the sample interval of the data. This makes it easier to infer the time-series properties of the fault signal with the residuals, compared to the sensor outputs. In this study, an FDI system first generates residuals using EKF (Extended Kalman Filter). Then it evaluates the residuals by classification using deep learning. As for the architecture of deep learning, LSTM (Long Short-Term Memory) is used to evaluate a time series of a dynamic system. The LSTM tries to find an approximation of a function that maps the time series of this residual into the estimated probability of each fault category. The results show that the FDI with residual can diagnose some of the sensor faults more accurately with a small amount of data than the FDI with sensor outputs.