



ORBIT-STAR: AI powered FDIR

Executive Summary Report

Early technology project for future orbital missions

New concepts for onboard software development

Affiliation(s): Airbus Defence and Space (Prime)

Activity summary:

Artificial intelligence has the potential to become an integral part of space in the future to realize the autonomy of the system without ground control and crew interactions. The demonstrator developed in the scope of the ORBIT-STAR project supports the evaluation of scenarios and techniques for incorporating machine learning algorithms in an operational environment. The demonstrator provides an execution platform for hosting AI-based applications and establishes the interface with the COLUMBUS module of the International Space Station to receive sensor data and send event messages to ground and crew.

The project was in the same time the pilot for the utilization of the platform for the evaluation of an anomaly detection and analysis use case for a selected COLUMBUS sensor data set. The applications were tested on the COLUMBUS Software Integration and Test Environment which delivered valuable information about the benefits and the pitfalls of the platform and the applications. The evaluation shows that if the platform can be further strengthened, it can be used to support experiments with AI applications and potentially even support operators in the maintenance of the station on-board.



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Abstract: This document provides a summary of the objectives of the ORBIT-STAR project, the methods employed, the results obtained and possible future work topics

Verantwortliche(r)
Inhalt: T.Manthey **Rolle¹:** FLT SW Engineer **Unternehmen:** Airbus Defence and
Content Responsible: **Role:** **Company:** Space GmbH

Verantwortliche(r)
Data Engineer: C.Haskamp **Rolle:** AI and data Engineer **Unternehmen:** Airbus Defence and
Company: Space GmbH

Verantwortliche(r)
TM Engineer: A.Lasserre **Rolle:** TM Engineer **Unternehmen:** Airbus Defence and
Company: Space Ltd.

Projectmanager
Project Responsible: D.Hofmann **Rolle:** Project Manager **Unternehmen:** Airbus Defence and
Company: Space GmbH

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1. Objectives and Approach

Orbit Star throws its light to support us in our endeavor with a lot of unknowns and uncertainties to incorporate AI techniques in space systems.

The ORBIT-STAR team has realized the objectives of the project aiming at providing an early technology demonstrator for AI-supported FDIR using the COLUMBUS module as a target system as follows:

- 1) The team has developed and set-up an execution platform for AI applications, which provides an IP-based interface to the COLUMBUS module to receive its data and notify Ground and Crew or even command the system to any applications running on it. Existing infrastructure on Columbus, such as the crew laptop hardware and software were used to facilitate the deployment and integration. The new generation laptop, an HP Z-Book G9 providing more processing resources was used. Therefore, the crew laptop software, which has not been ported for this platform yet, was virtualized and run in a virtual machine on the new hardware.
- 2) To show how the platform can be exploited and gain experience with user and system interaction, we have developed two applications complementing each other to enhance the on-board FDIR function. One application detects onboard anomalies based on life sensor data streams with machine learning algorithms and the other one, in case an anomaly is detected, analyses history data from anomaly reports and ground logs to provide related information about the anomaly to users.

2. Results and Conclusions

Nearly all functions defined to be realized by the demonstrator were implemented and validated to the extend achievable in the scope of this project.

Functions, which were not realized due to project resources constrains and export control restrictions on log data, are:

- Containerization of the anomaly detection application and run-time environment
- Full text search and analysis of the content of the historical data for finding related information for an anomaly in non-annotated logs

The end-to-end validation of the demonstrator on the Columbus Software Integration and Test Environment demonstrated that the AI platform can be relatively seamlessly integrated into the Columbus Data Handling System. Only some minor problems were observed with respect to the integration, such as time synchronization errors of the virtualized crew laptop and unexpected simulator behavior. These problems did not influence the functionality of the AI applications. They should be, however, further investigated in case any of the affected components are further used.

The E2E test results also showed that the AI-based anomaly detection can be used as an extension for the hard-coded FDIR failure detection mechanisms. The implemented anomaly detection application was able to recognize failures, such as larger drifts or irregular behavior of one of the sensors in comparison to the other. The hard-coded FDIR cannot recognize such anomalies. The AI-based anomaly detection raised relatively low false alarms, when "nominal" historical data was replayed. Failures detected by the standard FDIR mechanisms were detected also by the AI application.

The tests, which could be performed in the scope of the project, leave room for further tests with replayed data and more detailed analysis of the detected anomalies to improve the algorithms. Therefore, more test data needs to be labeled and analyzed.

The anomaly analysis application found and provided information from previous anomalies and command sequences from ground related to the detected anomaly based on annotated anomaly reports and log files. Thus, it was validated that the mechanisms and interfaces for accessing the anomaly reports and logs, parsing for the affected channels in the anomaly reports and parsing the ground logs for commands related to the anomalies successfully. The parsed files needed to be annotated on one side, because the ground logs did not contain any information on the purpose for sending these commands, for example troubleshooting for anomaly XYZ. Adding this information to the log files of future system development would help apply



automatic analysis and support decisions for dealing with an anomaly. The anomaly reports were annotated in this implementation to include directly the internal IDs of the affected channels for the anomaly, because they are also not always found in the reports. The reports usually use the OPS names of the measurements instead of the SIDs used by the DHS.

How these results from the onboard anomaly detection and related information mining can be operationally incorporated and used by the crew and ground control to support trend analysis and preventive maintenance can be further elaborated and analyzed.

2.1 Anomaly Detection Application

The outcome of the anomaly detection task of Orbit-STAR is a Columbus dataset consisting of five telemetry channels, including four different kinds of anomalies and rare events with a total of 25 occurrences. The period of time spans over 10 years, but not all the nominal telemetry data was extracted to keep the amount of data low. The collected data was pre-labeled from official anomaly reports but a post-processing was needed to enhance the labeling accuracy of that dataset. The start and end times of anomalies were optimized and the labeling was done according to the influence of anomalies for individual channels.

A pipeline for neural networks for time series anomaly detection data was implemented in the frame of Orbit-STAR. The main intention of the pipeline is to train neural networks and their evaluation. The inference is later done in another software framework. The pipeline includes the evaluation of trained networks on the test data. During the evaluation the anomaly score gets defined and thresholded. Finally different metrics are calculated and can be used to compare different neural networks or datasets.

The extracted dataset was based on telemetry channels that did not allow forecasting algorithms for anomaly detection. The reason is that from past telemetry data it is not possible to forecast the values of future data. This leads to the implementation of an autoencoder architecture, where the input signal of the network gets reduced by an encoder and afterwards decoded again to the original input. The expectation is that in nominal cases the network shows good performances while in anomalous cases the reconstruction will fail. The comparison of the input values and the reconstructed prediction gives an anomaly score that is used to define anomalous detections.

The trained network showed promising results for most of the test datasets, but had some limitations. The main limitation is that the reconstruction-based methods are not capable of detecting outages of individual sensors (leading to constant sensor values) when the second redundant sensor lies in a similar range.

One idea in Orbit-STAR was to detect individual channels that are affected by an anomaly. This information should be the input to the Report and TM Management system as a starting point for the detection of similar anomalies. In the end this approach was not working out smoothly, the main reason is that a clear identification will only be possible when forecasting based algorithms for the anomaly detection get used. In such cases the probability is higher that only the anomalous channels show a misalignment. It might also work for reconstruction-based algorithms but in our case, it was not working as well as we thought in the beginning. In all cases we defined as anomalies we had two redundant sensors and in the anomalous case only one sensor showed a malfunction. The anomaly detection algorithm learned that both sensors have similar signals in the nominal case. In our error cases that led to reconstructed sensor values that are in between of both sensor values, which led to anomaly detections in both channels instead of only the malfunctional sensor.

One challenge in this project was the creation of a dataset for the anomaly detection application. As the budget of this project was limited it was not foreseen to use large portions of the Columbus telemetry data, mainly to keep the effort within the budget scope of the project. In the end this leads to extra effort in later stages of the project, as additional telemetry data would have been helpful to define rare events that were detected as anomalies in earlier phases of the project and should be marked as rare events. In future projects it makes sense to collect all data that potentially could be useful without using such data. Later usage of such data is then easily possible, because no additional data must be requested and be pre-processed again.

2.2 Reporting and TM Management

The functions implemented by the RT2M application encompass the search in historical anomaly engineering records and ground command logs to provide more information on the detected anomaly. Multiple pieces of information are added in the Anomaly Reports and Ground Logs to allow making links between new detected anomalies and these logs.



Anomaly Reports:

A new string listing all the affected channel SIDs: This has been added to all the generated anomaly reports as this allows the RT2M to effectively make a comparison between the report and the current detected anomaly.

Ground Logs:

Report ID Command Field Key: Each generated ground log xml file consists an additional Report ID key that contains the associated anomaly report ID. This establishes another link between the anomaly reports and ground logs which

the RT2M can use when obtaining associated commands related to previous occurrences.

Affected Channels String: A string field for the list of affected channel SIDs has also been added which adds another link between the reports and ground logs. The RT2M will use both these added fields to verify the report associated with the current command ground log.

Therefore, the Report and TM Management software demonstrates required capabilities but needs supplementary data to be added to the on-board logs in order to function properly.

For future versions, the possibility of adding the described pieces of information in Anomaly Reports and Ground Logs by Ground Operators can be considered as well as improving the RT2M to avoid requiring such data.

2.3 Future Work

The ORBIT-STAR demonstrator is the first step towards an in-flight execution platform for AI applications. To proceed with this next step, the demonstrator has to be enhanced and made secure and robust to provide adequate operational interfaces for crew and ground to update and configure, activate and deactivate the AI platform and applications.

The aim of Orbit-STAR is to demonstrate the overall workflow of an anomaly detection and reporting application running on the execution platform. During the project only a limited number of anomalies and their corresponding telemetry channels could be processed and analyzed. A next step would be the scaling of such a system to handle a realistic amount of data (e.g., number of telemetry channels, anomaly reports, different types of anomalies, etc.). This must be accompanied with the implementation of additional anomaly detection algorithm to allow the detection of multiple different anomalies.

This project showed that using existing anomaly reports is not sufficient, as during their creation it was never thought of using them for automatic analysis. The included information might be not sufficient for the detection of correlating anomalies, reasons for that are:

No definition of affected telemetry channels, only some of the relevant channels are documented in the anomaly reports.

Depending on the implemented anomaly detection algorithm, the affected channels might vary. Reconstruction-based methods are expected to have differences compared to forecasting-based methods.

Due to this, it is expected that a pre-processing of past anomaly reports is necessary. Such a processing could be a classification of known anomalies or the automated update of the anomaly reports based on the anomaly detection results applied to older anomaly reports.

More sophisticated techniques, such as information retrieval, deep learning and large data models for data mining and data correlation can be adopted for extracting and formulating information from historical data and logs related to anomalies. Further information sources used also for example in trend analysis, currently performed manually, can be analyzed and methods for their automatic analysis can be defined.

Finally, the experience gained throughout this project can be applied also to other spacecraft types, such as satellites to define the process, ground tools and environments for the development of such platforms in other space domains.