Towards comprehensive AI-based onboard FDIR: system design and first results

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AIKO

INFINITE WAYS TO AUTONOMY

Introduction

Health monitoring of spacecrafts is a crucial task in Space operations. Fault Detection, Isolation and Recovery (FDIR) plays a critical role in ensuring the safety and successful operation of a spacecraft by detecting and isolating faults, and then executing recovery actions. Currently, the FDIR process is carried out mostly on ground, with only anomaly detection typically performed onboard the spacecraft using out-of-limit (OOL) threshold techniques, whereas fault isolation and recovery is managed by operators on the ground.

This approach has two major limitations. Firstly, OOL approach is not capable of identifying subtle anomalies that occur within the parameters' nominal operational range, limiting its effectivity in identifying a wide range of anomalies. Secondly, the need for ground investigation to isolate the fault prior to the implementation of a recovery action introduces a delay in the overall FDIR pipeline.

Overview

In this work, we propose an AI-based onboard FDIR solution capable of detecting and identifying anomalies, and to suggest recovery actions in complete autonomy. It is composed of two main modules: a Sensing Service, responsible for anomaly detection, and a Reasoning Service, which deals with isolation and recovery.

The Sensing Service relies on Deep Learning algorithms trained on nominal telemetry data to perform time-series forecasting. During inference, anomalous patterns are identified employing a reconstruction-based error technique. This solution allows to identify a wider range of anomalies with respect to traditional OOL techniques.

The Reasoning Service is triggered upon reception of an alert from the Sensing Service. The central component is represented by a Knowledge-Based System that validates the alert against false-positives and infers the most likely root causes for the anomaly. Given the classification output, the Reasoning Service determines suggestions on the best recovery action, that can be immediately applied or communicated to the ground for validation.

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Traditional FDIR

The FDIR process comprises three main functions: Detection, Identification, and Recovery. Traditional FDIR systems onboard spacecrafts implement only limited detection capabilities (Figure 1). Upon detection, automatic actions are usually taken to ensure the safety of the asset, which usually consists in triggering the transition to a lower operating mode where the anomalous component or subsystem is deactivated or excluded. Anomaly investigation, identification, and recovery are then performed on the ground by operators based on data downlinked to the control centre. In addition, subtle anomalies might go undetected onboard and only be discovered by human inspection.

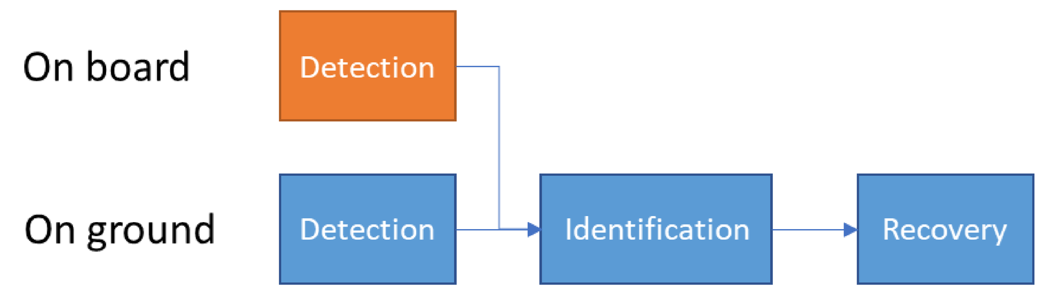

Figure 1. Traditional FDIR approach.

AI-based onboard FDIR

By largely relying on ground-in-the-loop, the traditional FDIR process is prone to long intervals between anomaly occurrence and solution, during which the spacecraft is unavailable or operating with reduced efficiency. Our system aims to move all FDIR functions on board as much as possible (Figure 3). In particular, it shall be able to reliably discover a large set of anomaly classes thanks to advanced detection capabilities. Moreover, automatic identification is mandatory to enable automatic recovery without human-in-the-loop. In addition to post-event analysis and continuous monitoring, human intervention is still foreseen in the recovery step.

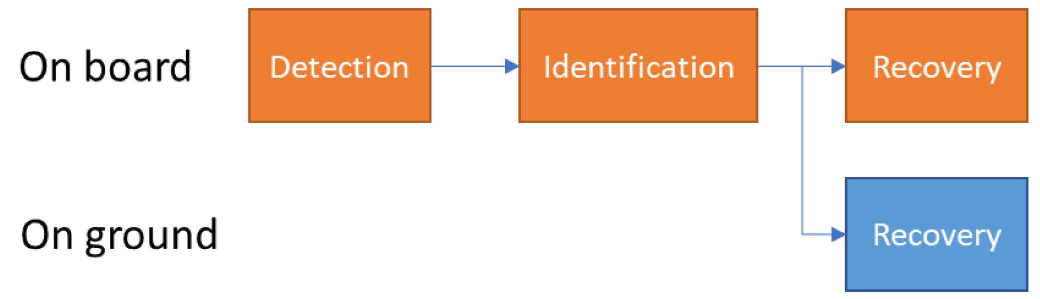

Figure 2. Onboard FDIR approach.

In order to fully detect and identify anomalies, and to suggest recovery actions, the envisioned architecture implements a two-step approach that exploits its Sensing and Reasoning Services. Specifically, the Sensing Service is responsible for anomaly detection, while the Reasoning Service performs isolation and recovery functions.

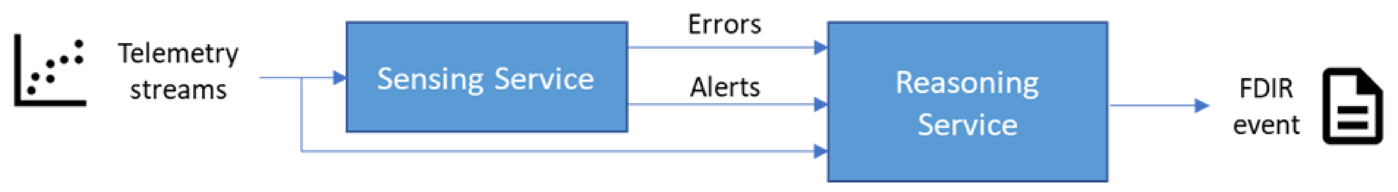

Figure 3. Two-step FDIR approach: Sensing and Reasoning service.

The central component of the Sensing Service is a Deep Learning (DL) model, whose role is to predict the future nominal evolution of selected satellite's telemetry points. Concerning the Reasoning Service instead, the central components is characterized by a Knowledge-Based System (KBS), in charge of classifying the detection performed at Sensing level.

Use case description

We applied the developed system architecture to a use case aimed at identifying anomalies related to the Attitude, Determination and Control Subsystem (ADCS) of a 6U satellite. In particular, the goal was to detect and classify the among different anomaly types:

- **Reaction Wheel (RW)**: nominal strain, controller instability, wheel stiction, desaturation and detumbling
- **Inertial Measurement Unit (IMU)**: stuck and out-of-scale IMU
- **Solar Angle Sensor (SAS)**: stuck SAS and silent stuck SAS

The available dataset comprises of both real anomalies experienced by different satellites, as well as synthetic examples generated trhough a Flatsat. A total of 83 faults are available, divided between 12 real and 71 synthetic examples. Additionally, dataset containing only nominal behaviour of the dataset are available, which are used to train the DL model, core of the Sensing Service.

Results

The results obtained running the AI-based FDIR approach proposed in this work have been compared to the ones obtained using the traditional FDIR, implemented on current spacecrafts' missions.

Table 1 shows the results in terms of number of better or worse detections with respect to traditional FDIR (in terms of response timing), undetected anomalies, and correctly classified and unclassified detections.

Table 1. AI-based detection and classification results.

CASE	#	Better	Worse	Undetected	Correct	Wrong
Controller instability	13	12	0	1	11	1
Wheel stiction	4	4	0	0	4	0
Nominal strain	3	-	-	-	-	-
Desaturation	11	10	1	0	4	7
Detumbling	10	9	0	1	9	0
Stuck IMU	11	0	11	0	9	2
Out-of-scale IMU	11	8	3	0	2	8
Stuck SAS	10	4	0	6	4	0
Silent stuck SAS	10	10	0	0	10	0

Table 2 shows the results in terms of number detection and classification delay with respect to the actual start of the anomaly and the FDIR detection.

Table 2. Response timing wrt anomaly and FDIR detection.

CASE	#	Anomaly	FDIR
Controller instability	13	11.2 min	-inf
Wheel stiction	4	15 sec	-45 sec
Nominal strain	3	-	-
Desaturation	11	48.8 min	-35.5 min
Detumbling	10	20 sec	-
Stuck IMU	11	5.1 min	4.6 min
Out-of-scale IMU	11	16.6 min	13.6 min
Stuck SAS	10	24.0 min	-
Silent stuck SAS	10	17.5 min	-inf

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