

DMSS: Decision Management System for Safer Spacecrafts

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Abstract. The fast growing number of low earth orbit exploitation and deep space missions results in enormous volumes of telemetry data. In order to operate efficiently satellites constellations as well as spacecrafts, DMSS offers a self-learning visual platform for anomaly detection in telemetry data coming from embedded sensors. As use-case, the data of two space missions operated by the European Space Agency were analyzed: Mars Express and GAIA.

Keywords: Spacecraft telemetry · Anomaly detection · Visualization.

1 Introduction

Traditionally, mission control systems only monitor incoming telemetry measurements against pre-defined soft and hard limits. Spacecraft operator engineers (SOE) are warned in real-time and in out-of-limit logs when telemetry parameters go out of limit [12]. Then they have to check manually if it corresponds to a real anomaly.

Recently, the increase in downlink bandwidth and available processing power on space platforms has resulted in an increase in the number of telemetry measurements available to monitor the health and safety of spacecraft. With more and more on-board sensors (typically in the order of tens of thousands), it becomes impossible to check manually all potential anomalies on a daily basis. As a result, automatic checks and computer-assisted data analysis are needed to help SOE to detect anomalies in telemetry series at an early stage, improving the likelihood that measures can be taken to prolong the lifetime of the spacecraft.

The rest of this article is organized as follows. Firstly, related works about telemetry data analysis are mentioned. Then, the architecture of DMSS is presented. Finally, two use-cases are shown through the developed user interface.

2 Related works

Various approaches and tools were recently proposed to inspect spacecraft telemetry data, and especially for anomalies detection:

- Fine-grain visualization platform to inspect telemetry time series [11].
- Data-driven extraction of dependencies in mission parameters [10].
- System based on LSTM Neural Networks was deployed by NASA to control the Curiosity rover operated by NASA [6].
- Application of a fully automatized data processing workflow [1].
- Forecasting of telemetry parameters values [7].

Additionally, several tools have been developed by the European Space Agency to support their activity, and many of them are based on MUST, a framework to efficiently manage space missions telemetry data [9].

In this work, we propose with DMSS an interactive web application allowing SOE to investigate the results of automatic anomalies calculations and to perform data selections in order to visually detect correlations with anomalies. To avoid saturating the spacecraft operator engineers (SOE) with many false positives [6], DMSS focuses on guiding the SOE towards the *most relevant* potential anomalies of the day.

3 Approach and Software Architecture

DMSS is composed of three components (Fig. 1), each of them being developed upon the appropriated technology [3]:

- A Python batch analytical engine ingests the raw mission data coming from the spacecraft sensors and it pre-calculates daily anomaly scores for each telemetry parameter following a method developed by Katholieke Universiteit Leuven [12]. At the end, it stores the obtained results in a huge HDF5 database (HDF5 being an efficient format to manage telemetry data [5]).
- The Java-based Backend uses the previously generated HDF5 database and makes it available as *ready-to-visualize* data through a REST API by using SparkJava – a framework to build micro-services [13]. In order to optimize the data transmission, the Backend tries to minimize the bandwidth usage by applying simple well-known techniques like data caching or time series reduction (Ramer-Douglas-Peucker algorithm [4]).
- The web-based rich Frontend application allows SOEs to search and analyse anomalies in spacecraft telemetry data. Based on the node.js framework for the network communication [14] and using D3.js for the visualization [2], the Frontend interacts with the Backend according to the end-user actions.

In the next sections, two use-cases are quickly described and the DMSS user interface is presented.

4 Use-cases: Mars Express and GAIA

The telemetry data of two space missions operated by the European Space Agency were studied. The first one is Mars Express, a space scientific mission initially launched in 2003 to explore Mars. The second one is GAIA, an astrometry spacecraft operated since 2013. Its purpose is to build precise 3D space catalog.

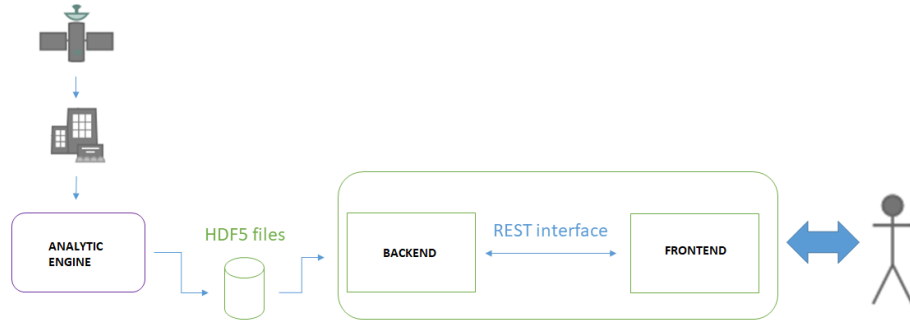


Fig. 1. The DMSS architecture: the analytical engine provides precomputed results to the Backend which pre-digests data for the interactive web-based Frontend.

In both cases, we have integrated in DMSS the telemetry parameters data of the missions for 2016 (5127 parameters i.e. 141 GB for Mars Express, 28209 parameters i.e. 1.46 TB of data for GAIA - including raw time series and statistical pre-calculations). For example, the number of points per time series is very variable, from a few samples up to 13 million samples.

5 User Interface

DMSS follows a Visual Analytics approach to help SOE to detect anomalies during mission control [8]. More precisely, DMSS provides visual representations of telemetry data and derived computational data under the form of interactive and connected diagrams (such as Poincaré plots, KDE schemas, Heatmap, and time series). The interactivity and the connectivity are both materialized by the fact that choosing data in one diagram highlights corresponding data in a related other diagram (Fig. 2). For instance, selecting data in the the Poincaré Plot automatically highlight the corresponding information in the KDE schema.

In order to facilitate the daily work of SOE, the main screen of DMSS presents an Heatmap displaying all telemetry anomaly scores for a specific day (Fig. 3). The goal is to quickly show which telemetry parameter potentially shows an uncommon behaviour.

More precisely, the Heatmap is a colored grid cell, each square represents a telemetry parameter anomaly score:

- Blue means that no anomaly score has been calculated for this date (due to missing or incomplete data).
- Grey means that the anomaly score is zero, the corresponding parameter has a standard behaviour for the selected date.
- Red means that the anomaly score is positive, this parameter has an uncommon behaviour, user should click on it to see more details and investigate more to see if it's due to an anomaly.

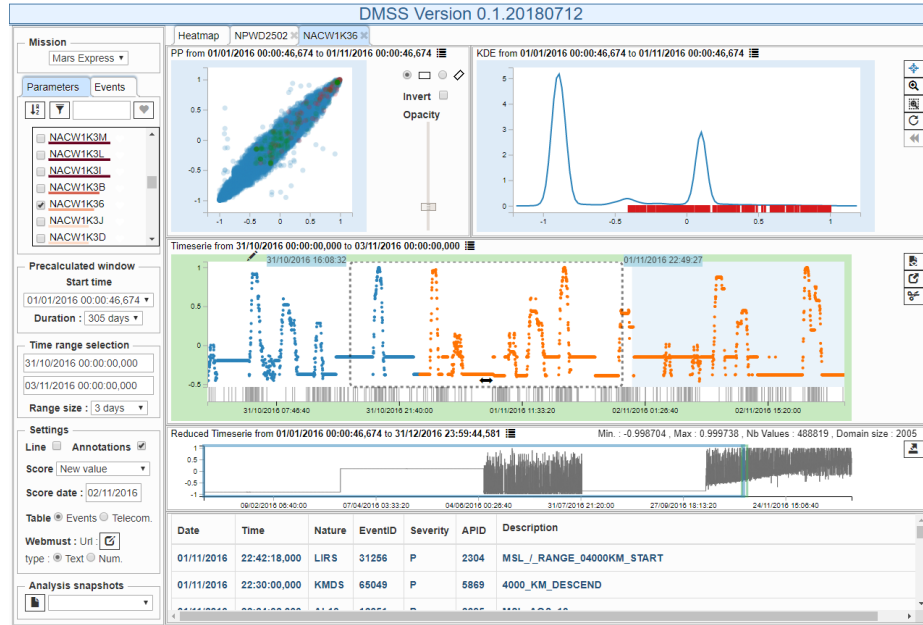


Fig. 2. The User Interface of DMSS: the user can select a time slot for a given telemetry parameter (green box) and visually see its status with the different plots.

- Green means that the anomaly score is negative, negative scores may occur for some score type when during the one or more days the anomaly score was positive and now the scoring system detects that the parameter behaviour is coming back to normal.

With this view, end-users can see if a group of telemetry parameters has a high anomaly score and also see if one specific telemetry parameter has an high score compared to other similar telemetry parameters.

If the case seems interesting for the SOE (i.e. synonym for potential existing or upcoming problem), then the current User Interface configuration can be stored in a *Snapshot* for further investigation.

Conclusion

DMSS helps to analyse large volumes of time series data coming from spacecraft sensors - which is a typical scenario for IoT applications. In this use case, operational risks are high, and efficient support of spacecraft operator engineers is of paramount importance. These requirements in terms of efficient software architecture and semi-automatic data analytics support are high. We reckon that the approach could be applied to a large extend in other IoT scenarios.

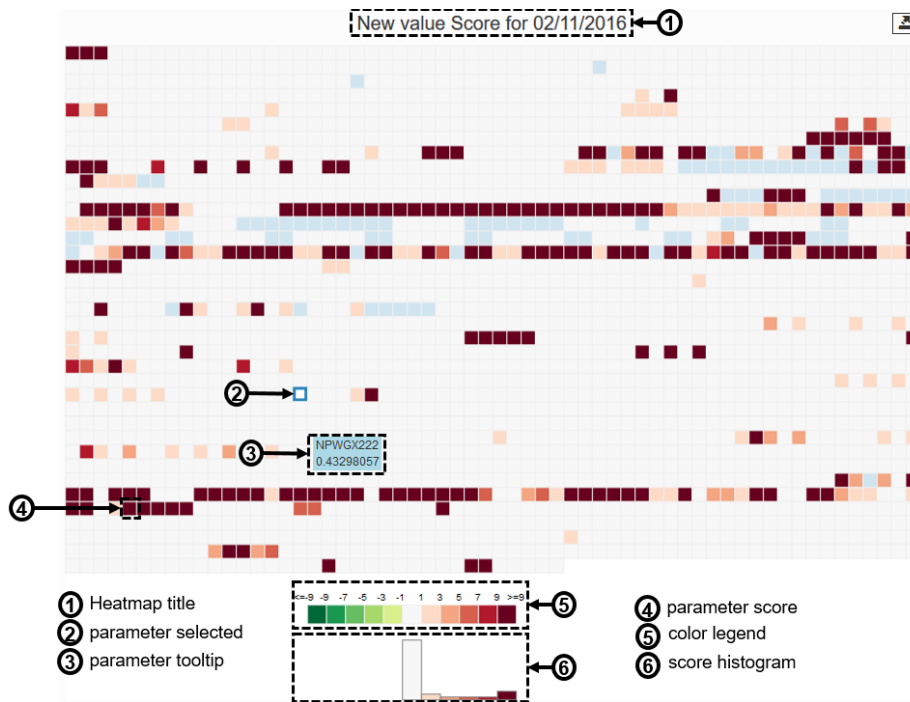


Fig. 3. The Heatmap for the Mars Express mission for 2/11/2016. This view is used to visually display all parameter anomalies in a single view for a specific day.

In further works, we plan to adapt the architecture of DMSS – and especially the analytic engine and the Backend – to apply recent data stream mining algorithms to detect anomalies.

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