

Introduction

Detecting anomalies in telemetry data captured on board satellites is pivotal for their safe operation, allows us to respond to failures quicker and may serve as the smart on-board compression of telemetry data to downlink its important parts. We need to deal with various types of anomalous events [1, 2] (Figure 1):

- In point anomalies, telemetry values fall outside the nominal operational range,
- Collective anomalies refer to the sequences of values that are anomalous,
- In contextual anomalies, the single values are anomalous in local neighborhood.

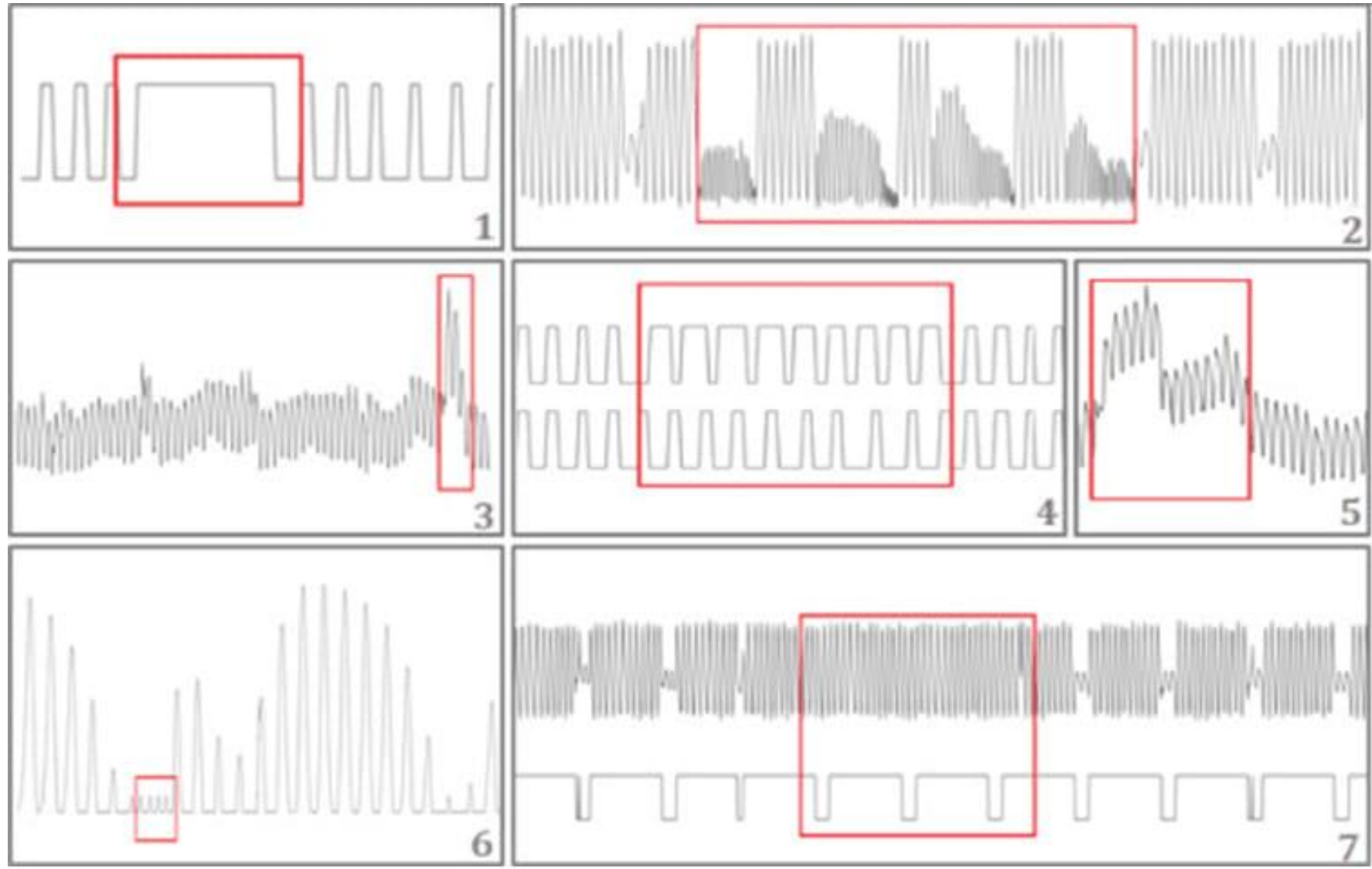


Figure 1: To effectively deal with on-board anomalies, we need to handle point, collective and contextual anomalous events, inherently different in their nature. (B. Pilastre et al. Anomaly detection in mixed telemetry data using a sparse representation and dictionary learning, Signal Proc., 168, 2020).

Failure Detection, Isolation and Recovery Systems (FDIRs) can exploit

- Out-of-limit checks (trivial to implement, extremely fast but require prior knowledge concerning the signal characteristics),
- Data-driven machine learning algorithms (require parameterization, may be computationally expensive, require training data for supervised training).

How to exploit machine learning for anomaly detection from real-life OPS-SAT data?

Case study: detecting anomalies in OPS-SAT

OPS-SAT (Figure 2) is a 3U CubeSat launched by ESA on December 18, 2019. The mission is to demonstrate the improvements in mission control capabilities that will arise when satellites fly more powerful on-board computers. As a flying laboratory, it will validate new techniques in mission control and on-board systems.

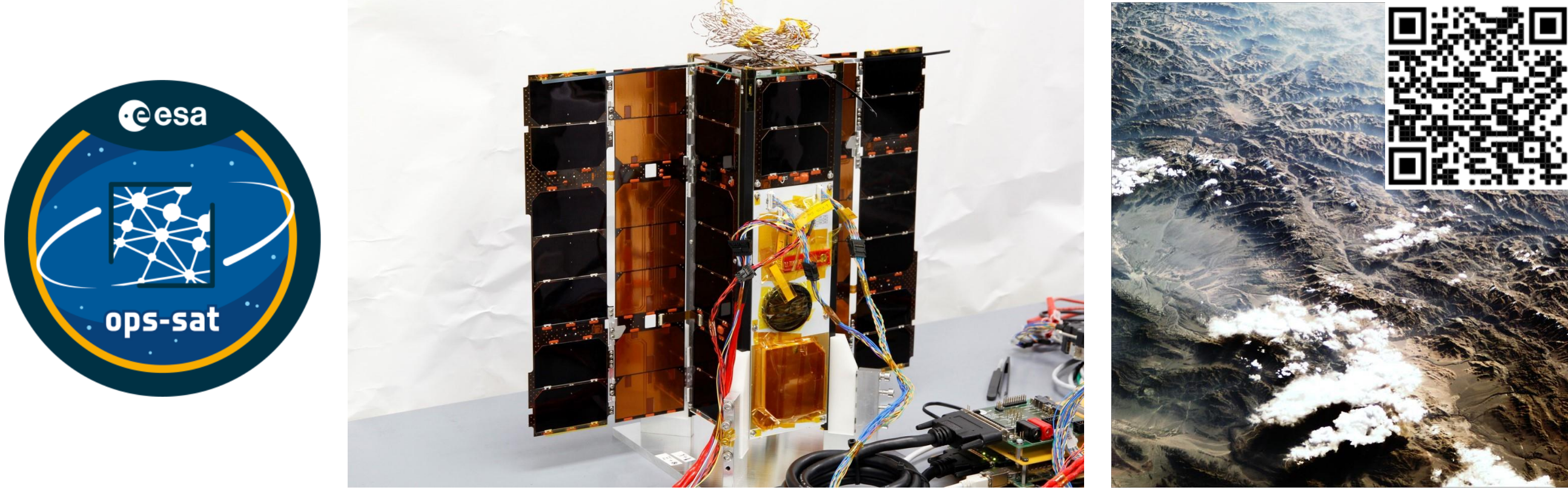


Figure 2: OPS-SAT is accessible by experimenters, and it is a fully open hardware and software innovation lab in Low Earth Orbit. Post-processed images acquired by OPS-SAT are regularly published on Flickr (see the QR code overlaid on the OPS-SAT image acquired over Argentina).

As OPS-SAT is an operational satellite, we can capture its real telemetry (Figure 3) to develop and validate automatic anomaly detection algorithms targeting OPS-SAT.

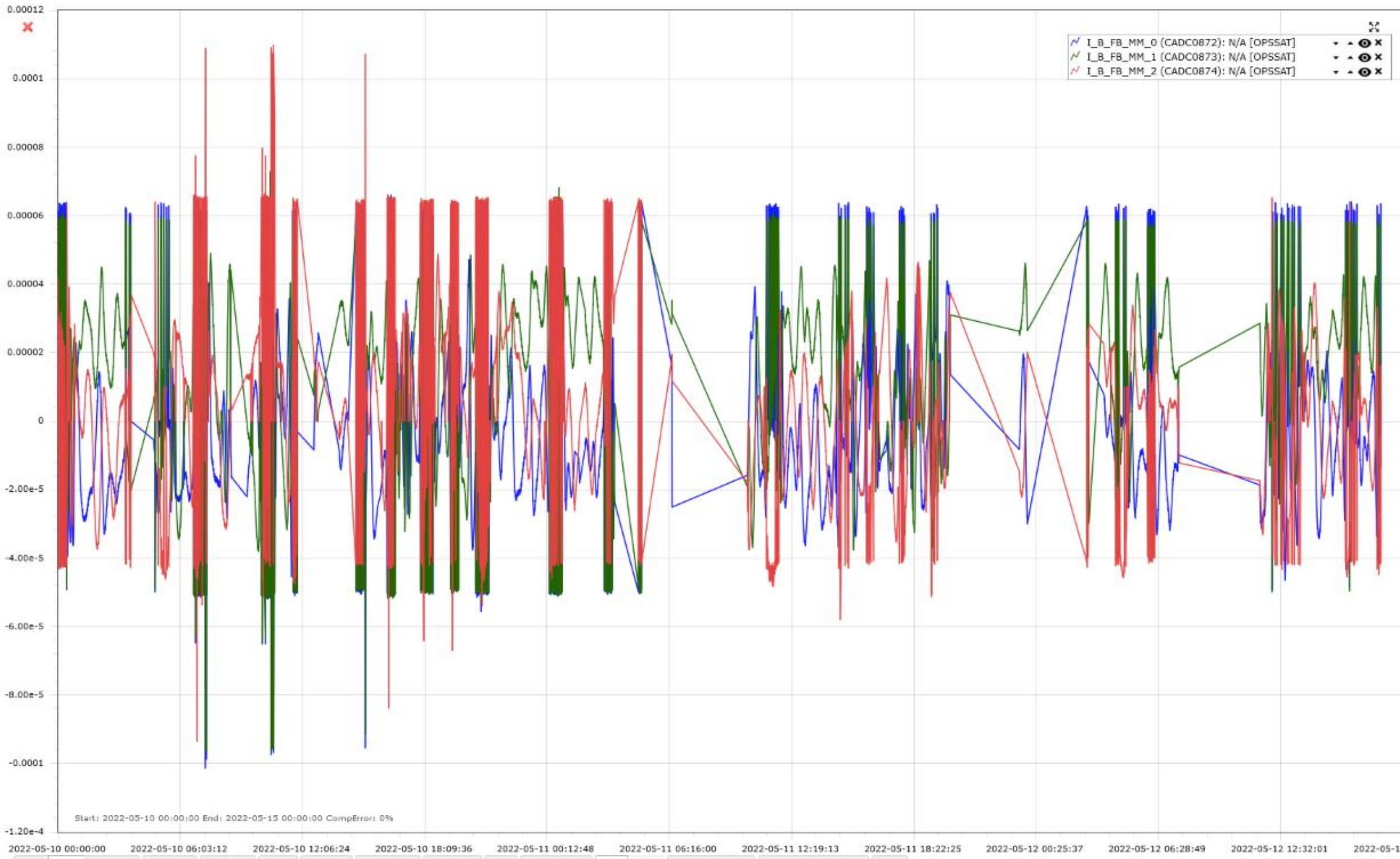


Figure 3: Preview of the example telemetry channels in the ESA MUST system. This example presents real-life challenges concerned with the telemetry channel data, such as missing values or unexpected peaks which may (or may not) correspond to the actual anomalous events.

OPS-SAT anomaly detection: dataset

We focus on the most interesting channels defined by OPS-SAT team (magnetometer and PD). The Anomaly Annotator by KP Labs was used to:

- Perform exploratory analysis of the OPS-SAT telemetry channels,
- Identify periodic parts of the OPS-SAT telemetry channels,
- Split the OPS-SAT telemetry channels into 829 training, 277 validation and 341 test segments,
- Label the extracted segments as nominal or abnormal.

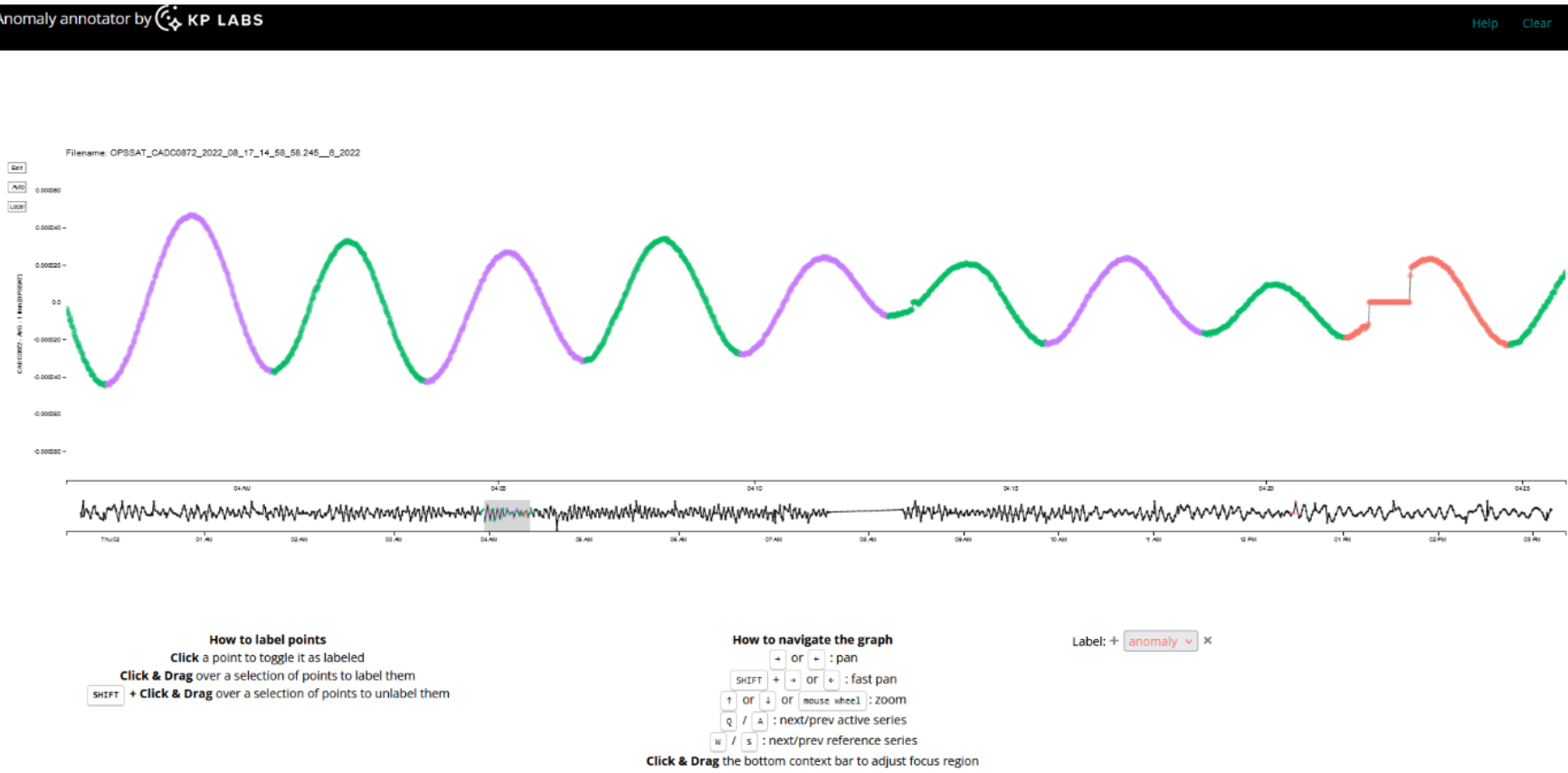


Table 1: The number of anomalous and nominal samples in the training, validation and test sets.

Subset	#Samples	#Anomalous	#Nominal
Training set	829	303	526
Validation set	277	115	162
Test set	341	293	48

Figure 4: Data Analysis in Anomaly Annotator by KP Labs – the data is split into segments and potential anomalies are labeled in red, nominal segments in green & violet (alternating).

OPS-SAT anomaly detection: experimental validation

To classify the telemetry segments into nominal and anomalous, we extract the following 16 features (independent of the length of the segment) which are fed into a random forest [3]:

- duration – in seconds alongside len – number of data points,
- mean, var, std – mean, variance, and standard deviation of the segment values,
- n_peaks – number of peaks of at least 10% prominence of the segment,
- smooth10_n_peaks/smooth20_n_peaks – number of peaks of at least 10% prominence of the smoothed segment (with the step value of 10/20),
- diff_peaks – number of peaks of at least 10% prominence of the first derivative,
- diff2_peaks – number of peaks of at least 10% prominence of the second derivative,
- diff_var – variance of the first derivative of the segment values,
- diff2_var – variance of the second derivative of the segment values,
- gaps_squared – sum of the squared of the gaps between the data points,
- len_weighted – length of the segment corrected using the sampling of the segment,
- var_div_duration – variance of the segment values divided by the segment's duration,
- var_div_len – variance of the segment values divided by length of the segment.

Table 2: Examples of true positive, false positive and false negative anomaly detections.

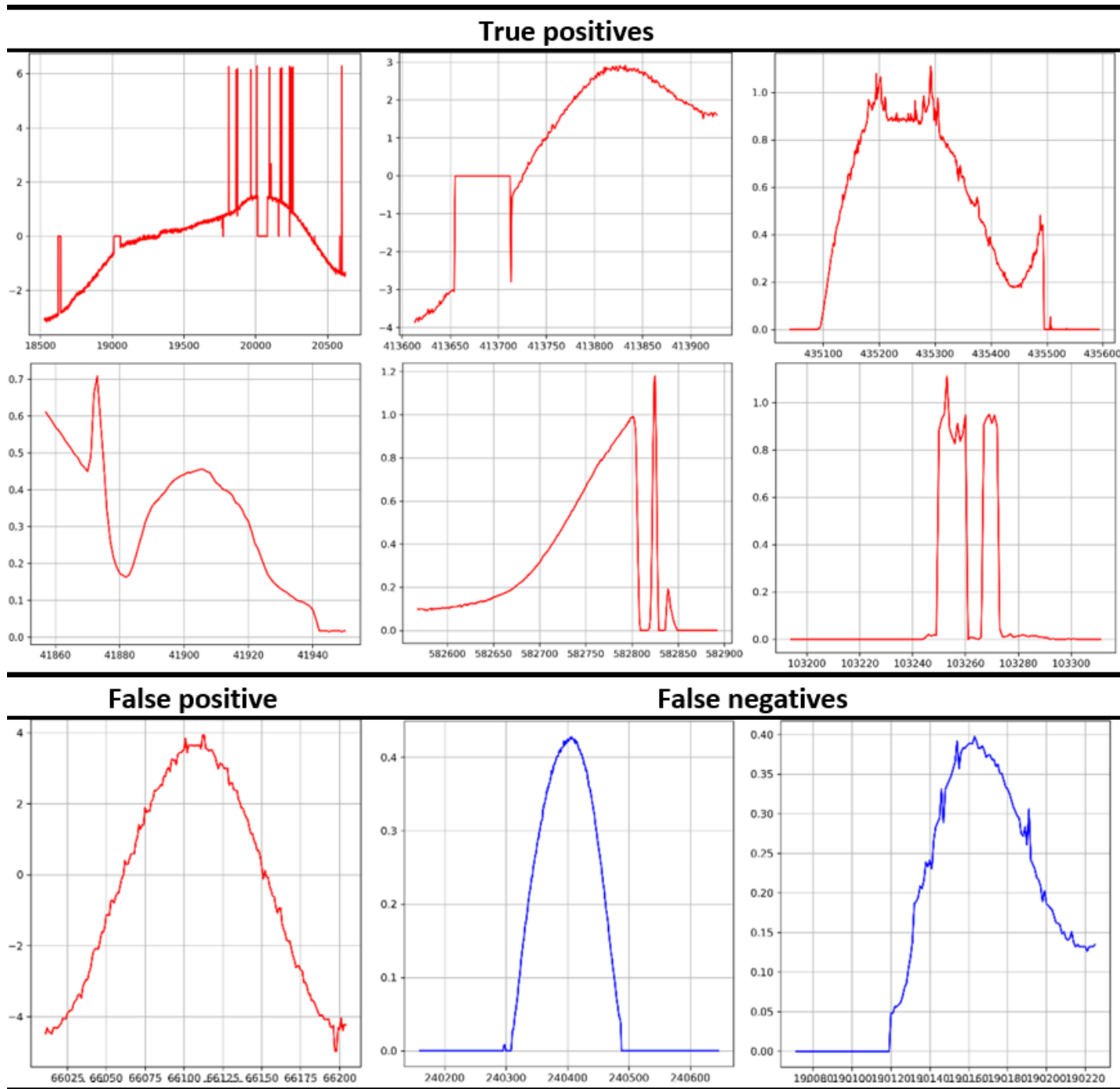


Figure 5: Correlation across the features quantified as the Spearman's coefficients for the training set.

For the validation set, the model reached the accuracy of 0.953, with the precision and recall of 0.964 and 0.922, respectively. Over the test set, the classifier reached accuracy of 0.938, with precision and recall of 0.986 and 0.942.

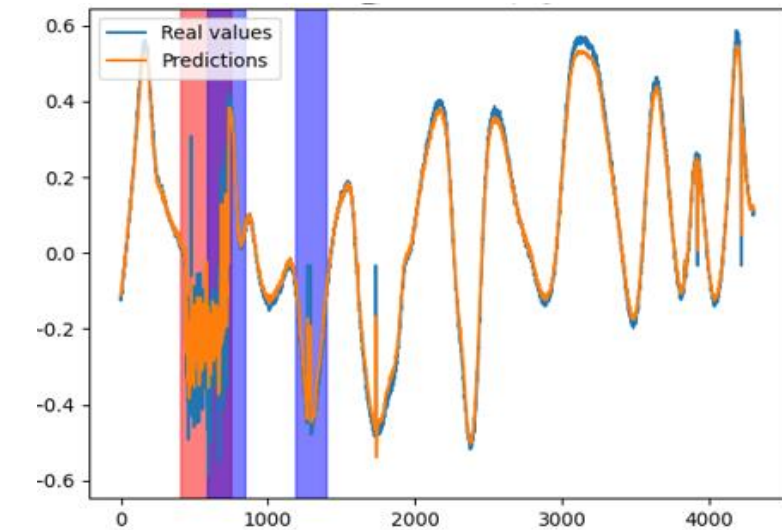
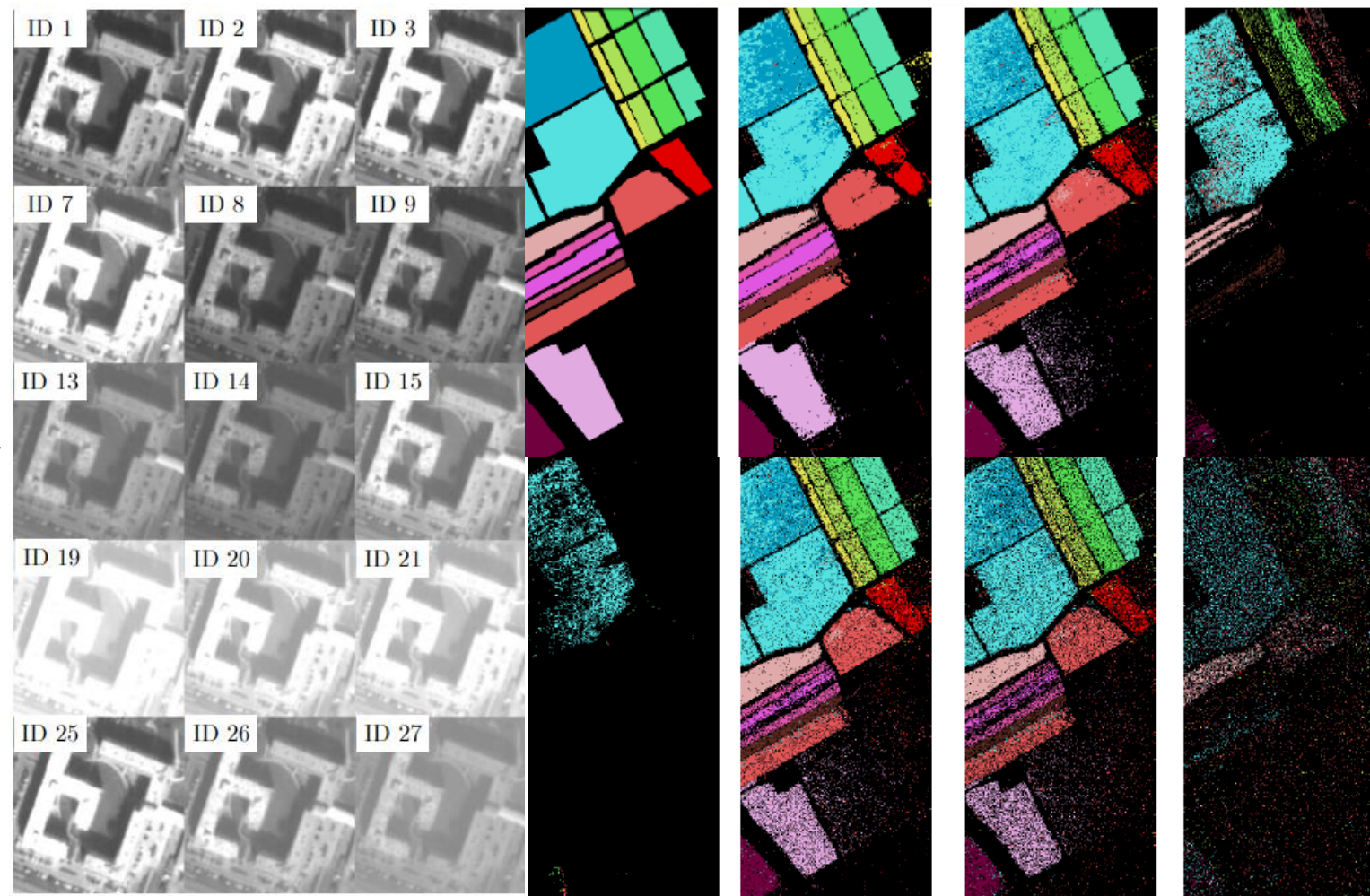
Author information and acknowledgements

- ¹KP Labs, Konarskiego 18C, 44-100 Gliwice, Poland, Email: {jnalepa, jandrzejewski, bruszczak, amusial}@kplabs.pl
²Silesian University of Technology, Akademicka 16, 44-100 Gliwice, Poland. Email: Jakub.Nalepa@polsl.pl
³Opole University of Technology, Prószkowska 76, 45-758 Opole, Poland, Email: b.ruszczak@po.edu.pl
⁴European Space Agency/ESOC, Robert-Bosch-Str. 5, 64293 Darmstadt, Germany, Email: {David.Evans, Sam.Bammens, Vladimir.Zelenevskiy}@esa.int
⁵Telespazio Germany GmbH, Europaplatz 5 64293 Darmstadt, Germany
⁶IrbGS Ltd, "Viraki", Ance parish, Irbene, Latvia, LV-3601



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Conclusion and future work: toward data-level digital twins



Our machine learning approach precisely detects anomalous parts of the telemetry channels, but does not detect the moment when the anomaly starts. Addressing this issue constitutes our current research efforts.

No ground truth? Why not simulate it!

Simulators, that reflect the characteristics of a real piece of hardware, can give us lots of advantages and are applicable to different data modalities (signal data, image data and so forth):

- We can simulate various acquisition scenarios (e.g., atmospheric conditions) [4].
- We can simulate noise, hence we can verify the robustness of the algorithms [4].
- We can simulate lots of data with precise ground truth information (imagine capturing the real life telemetry with all possible incorrect events for all hardware components...)

References

- [1] J. Nalepa et al., Acta Astronautica, vol. 198, September 2022, 689-701 (2022).
[2] S. Fuertes et al., AIAA 2016-2430, Adv. Technologies for Space Operations, 2016.
[3] K. Li et al., PLOS ONE 12(5): e0176614 (2017)
[6] J. Nalepa et al., Remote. Sens. 13(8): 1532 (2021)

For more our works on anomaly detection alongside the data sheets, see:

