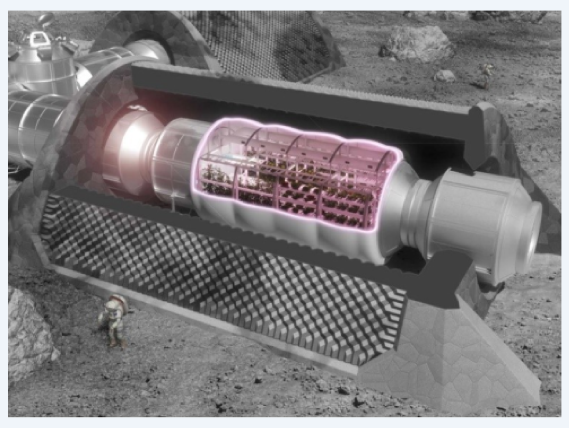
Unsupervised Anomaly Detection for Space Gardening

Introduction



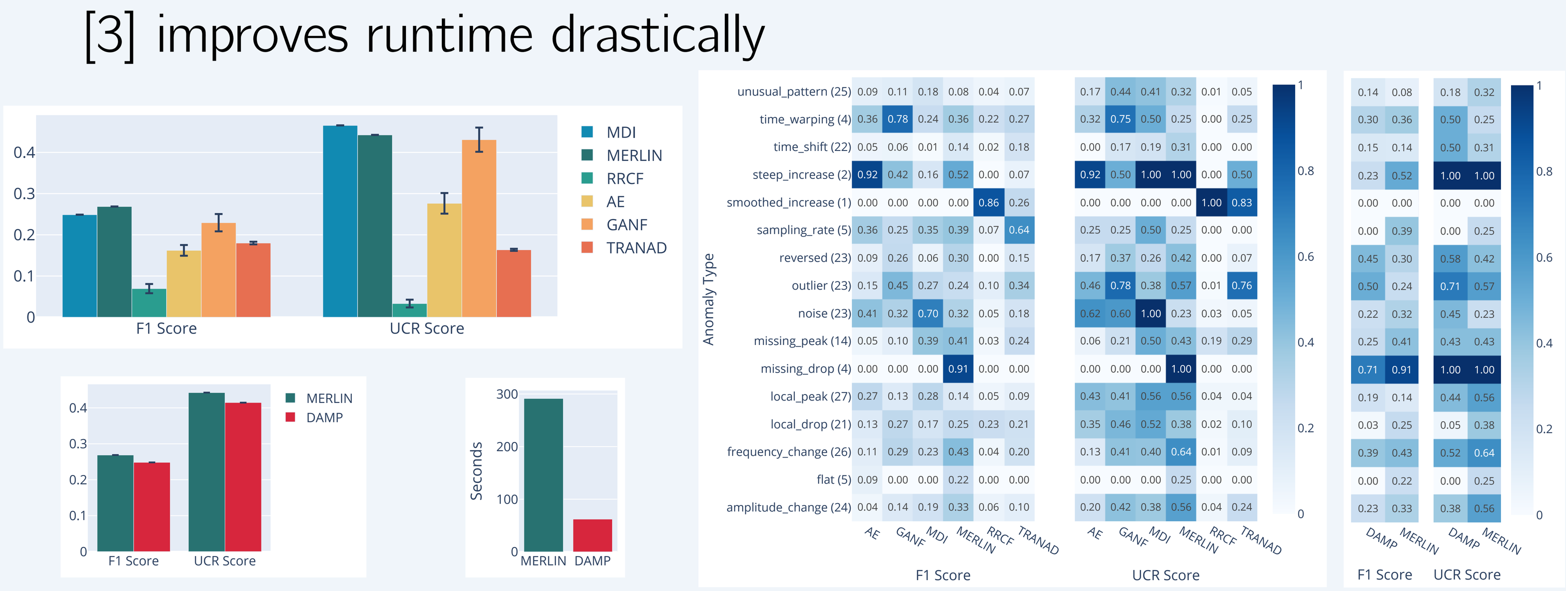
Bioregenerative Life Support Systems (BLSS) will be used within extra-terrestrial habitats to produce food, close material cycles (respiratory air, water, biomass, waste), and enhance well-being. The EDEN NEXT GEN project aims at designing an integrated BLSS ground demonstrator including all critical subsystems. Therefore, it builds on the results gained at the research greenhouse EDEN ISS in Antarctica between 2018 and 2021. To ensure safe and stable operation, we are researching **unsupervised anomaly detection (USAD)** methods to identify **unhealthy system states**.

While the abundance of available methods makes it difficult to choose the most appropriate method for a specific application, each method has its strengths in detecting anomalies of different types. We validate our previous findings from [5] in the BLSS domain and apply the best-performing methods to telemetry data collected from the EDEN ISS research greenhouse.

Benchmark Results

Our benchmark of six USAD methods on the UCR Anomaly Archive [6] dataset shows:

- Maximally Divergent Intervals (**MDI**)[1], **MERLIN**[4] and Graph Augmented Normalizing Flow (**GANF**)[2] perform best
- MDI and MERLIN are **synergetic**
- Swapping MERLIN with Discord Aware Matrix Profile (**DAMP**) [3] improves runtime drastically

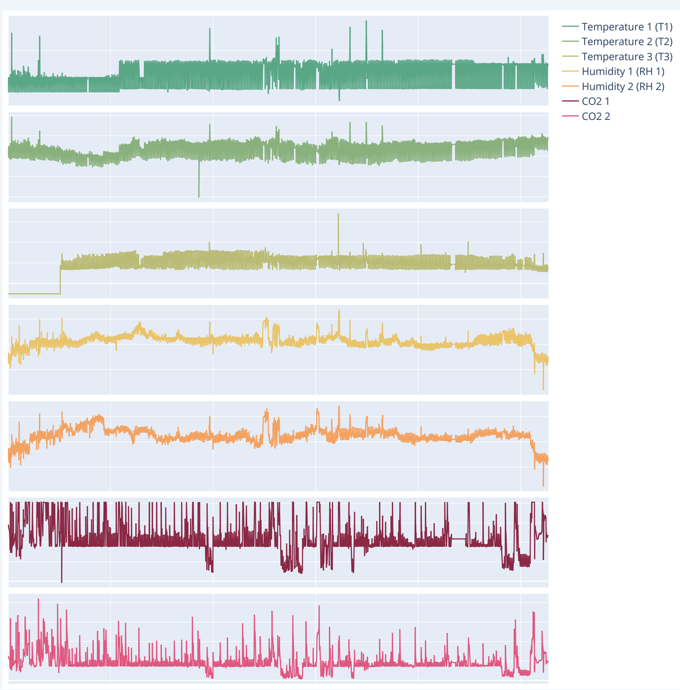


	mechanism	class	online/offline	training	multivariate	anomaly score
RRCF	Isolation Forest	classical	online	✗	✓	Collusive Displacement
MDI	Density Estimation	classical	offline	✗	✓	(KL/JS) Divergence
MERLIN	Discord Discovery	classical	offline	✗	✗	Discord Distance
AE	Reconstruction	deep-learning	offline training online inference	✓	✓	Reconstruction Loss
GANF	Density Estimation	deep-learning	offline training online inference	✓	✓	Density
TranAD	Reconstruction	deep-learning	offline training online inference	✓	✓	Reconstruction Loss
DAMP	Discord Discovery	classical	online	✗	✓	Discord Distance

EDEN ISS Data

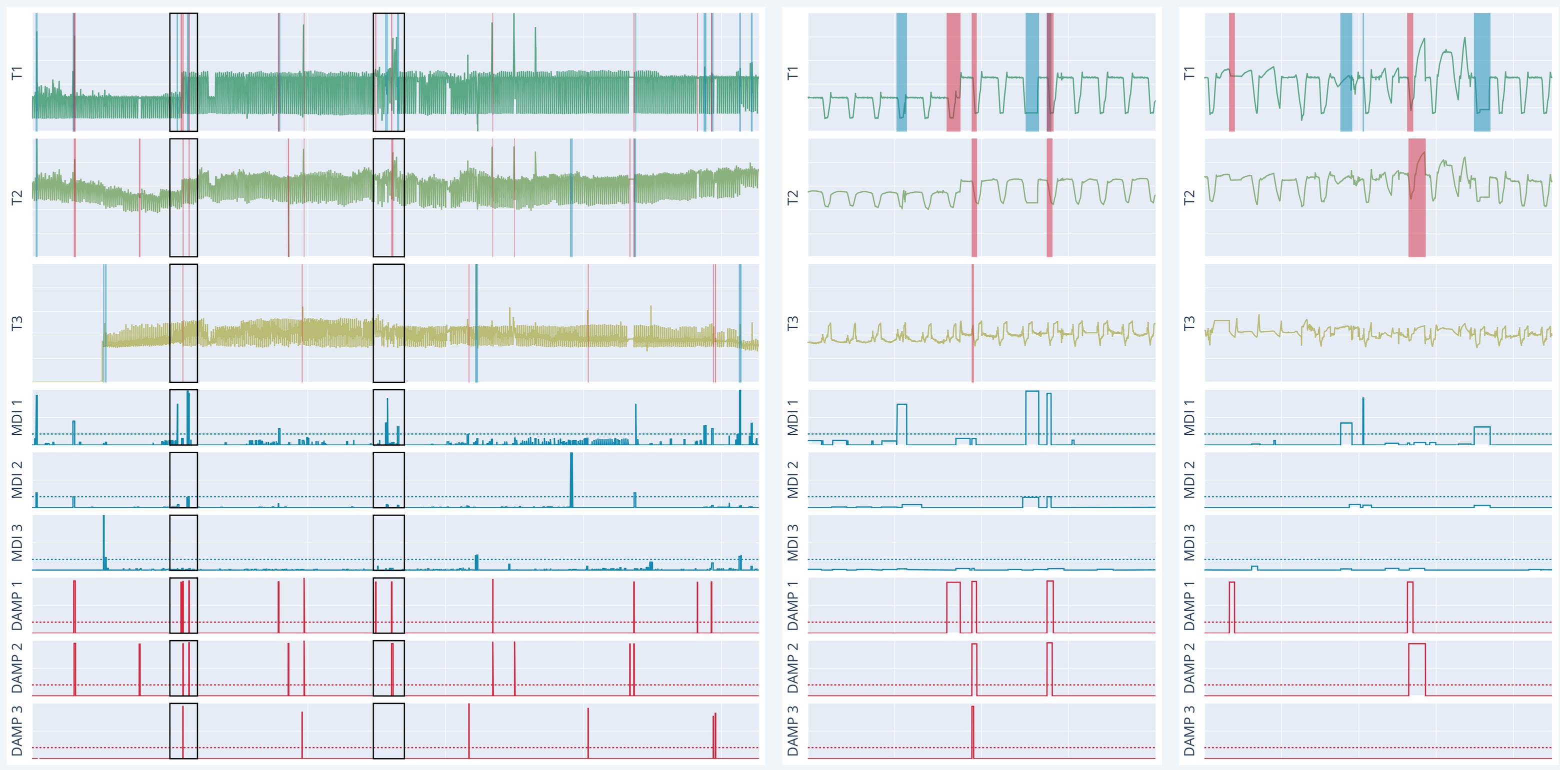
To validate our findings from [5], we applied MDI and DAMP to data from the EDEN ISS Atmosphere Management System (AMS) from 20210

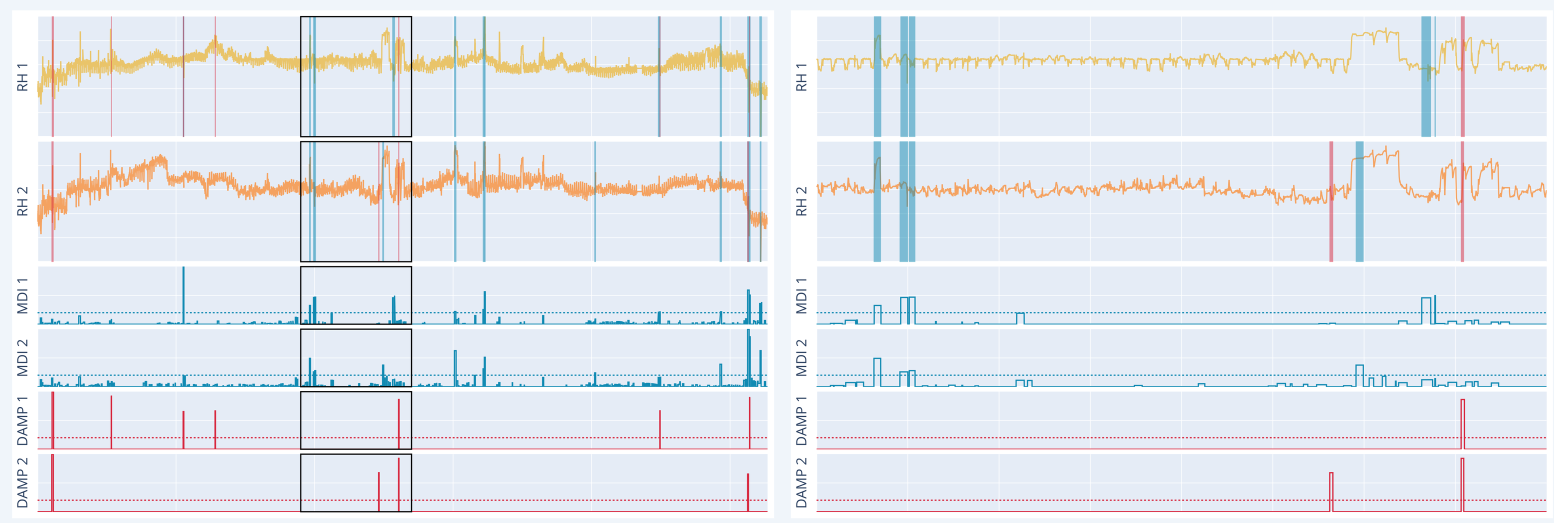
To account for the volatility of the data within 2020 and DAMP returning only the top-1 discord for a given time series, we applied both methods to monthly windows by shifting the window by one day on each iteration.



Results

For **Temperature** (first) and **Relative Humidity** (second), our expectations are met. MDI and DAMP highlight reasonable areas as anomalous. While both methods agree on some anomalous instances, others are found by either MDI or DAMP.





The results for the **CO^2** measurements are not as clear. As no ground truth is available and the time series doe not show a clear pattern, the assessment of the detections is challenging.

Outlook and Importance

To underpin our results on the AMS data, we will have them assessed by domain experts. Furthermore, we will apply MDI and MERLIN to the remaining time series from the Nutrition Delivery, Illumination, and Terminal Control Subsystems from EDEN ISS.

References:

[1] Björn Barz, Erik Rodner, Yanira Guanche Garcia, and Joachim Denzler. Detecting regions of maximal divergence for spatio-temporal anomaly detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2018.

[2] Enyan Dai and Jie Chen. Graph-Augmented Normalizing Flows for Anomaly Detection of Multiple Time Series. Sep 2021.

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[4] Takaaki Nakamura, Makoto Imamura, Ryan Mercer, and Eamonn Keogh. Merlin: Parameter-free discovery of arbitrary length anomalies in massive time series archives. In *2020 IEEE International Conference on Data Mining (ICDM)*. IEEE, 2020.

[5] Ferdinand Rewicki, Joachim Denzler, and Julia Niebling. Is it worth it? comparing six deep and classical methods for unsupervised anomaly detection in time series. *Applied Sciences*, 13(3), 2023.

[6] Renjie Wu and Eamonn Keogh. Current time series anomaly detection benchmarks are flawed and are creating the illusion of progress. *IEEE Transactions on Knowledge and Data Engineering*, 2021.

Ferdinand Rewicki[1,2], Joachim Denzler[2], Julia Fligge-Niebling[1]

ferdinand.rewicki@dlr.de

[1]Institute of Data Science, German Aerospace Center, Jena

[2] Institute of Computer Science, Friedrich-Schiller-University, Jena

DLR Deutsches Zentrum für Luft- und Raumfahrt German Aerospace Center

FRIEDRICH-SCHILLER-UNIVERSITÄT JENA