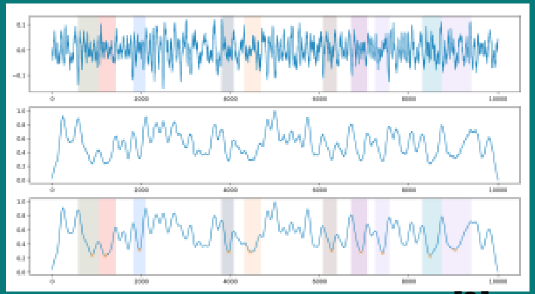
SAND2021-8087C

Sandia National Laboratories

Acoustic Signatures in Metal Laser-Powder Bed Fusion



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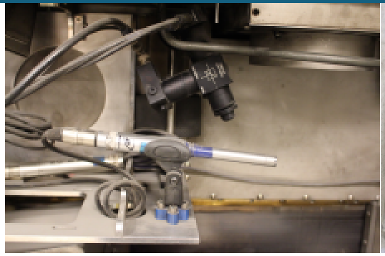

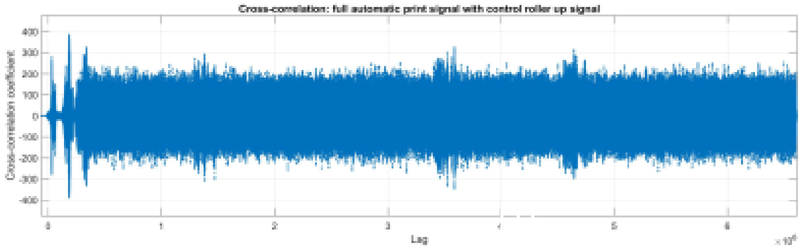

PRESENTED BY

Elaine Rhoades

S. Jensen, J. Pegues, B. Jared, D. Saiz, C. Brif, C. Zimmerman, M. Roach, M. Salloum

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Overview

General Process:

- Manual print several layers: pick up powder; deposit powder and level it with the roller; sinter the layer
- Automatic print: steps occur automatically, with powder pick-up occurring during laser firing (overlap in noise sources)

Project goals:

- Characterize acoustic noise from common sources of noise during an additive manufacturing process
- Create manual filters to remove noise from an acoustic signal collected during an automatic print
- Provide in situ monitoring for abnormal noise that might indicate a problem with the build

3D Systems ProX 200 Modifications

ARCS (Archive, Research, Control, Synchronization) System

- Laser motion

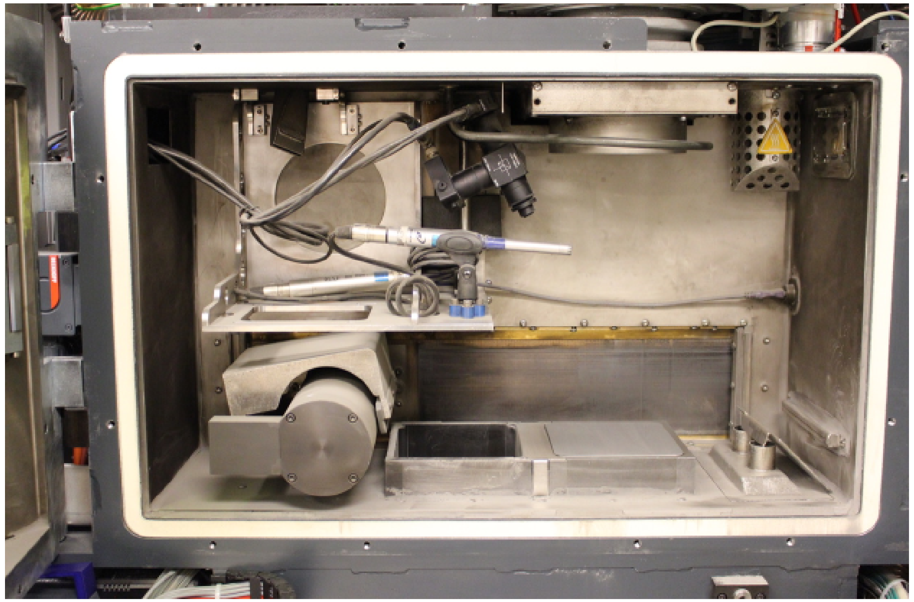
Two spectral sensors (520 nm & 530 nm)

- Melt pool

Virtins Technology EMM-6 microphone

Other equipment

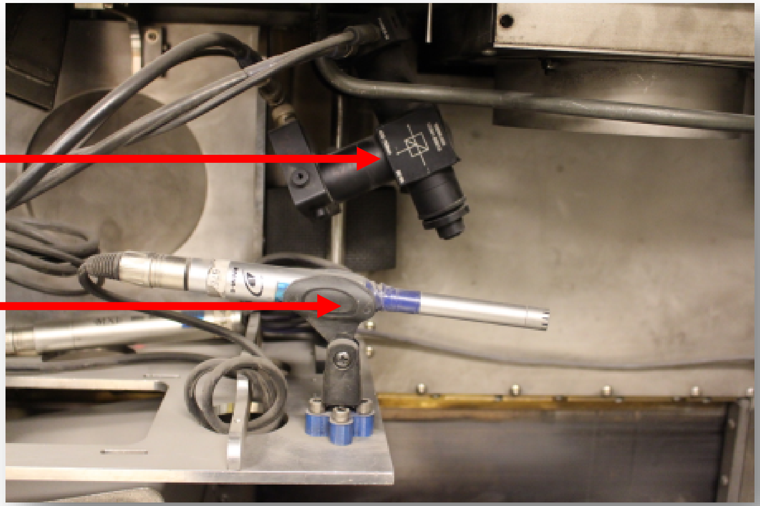
- NI PXIe-1085 power supply
- LabVIEW program (D. Saiz) for data acquisition
- MATLAB



ProX 200 Build Chamber

Spectral Sensors

Microphone

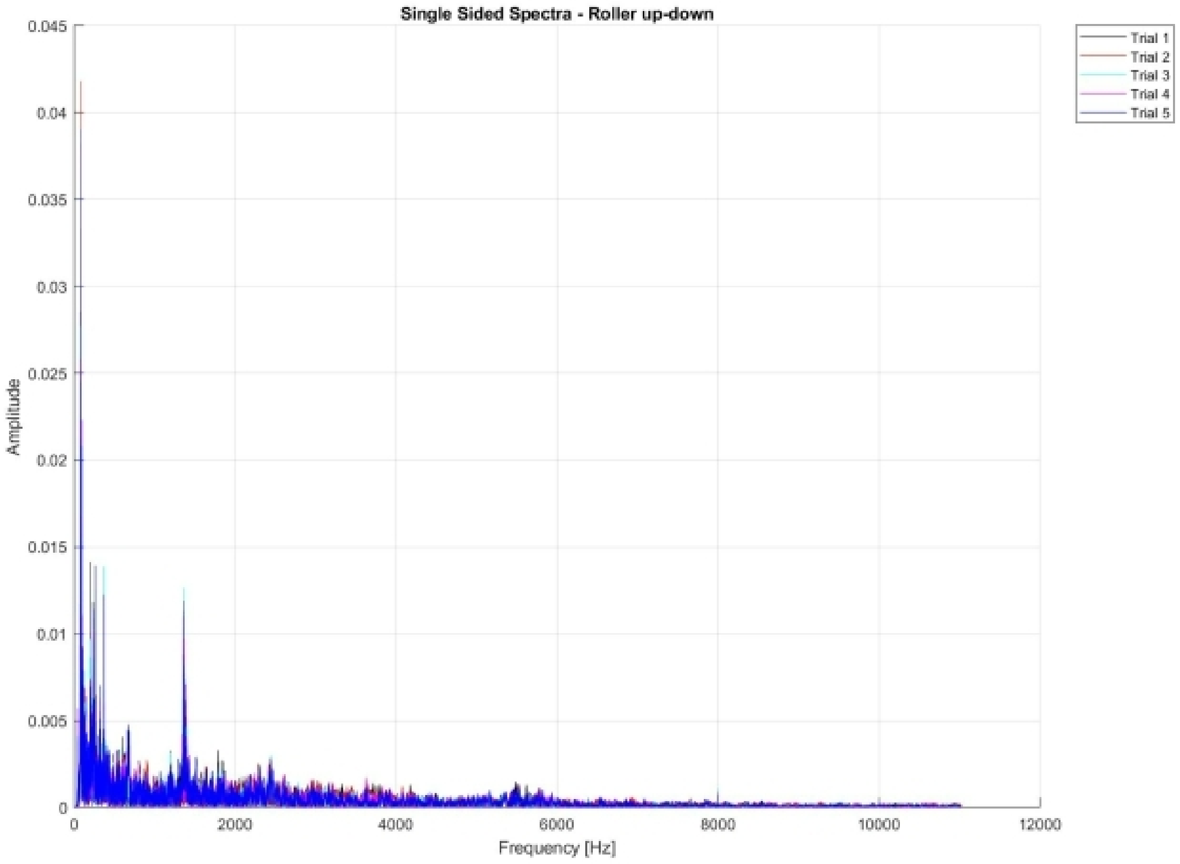


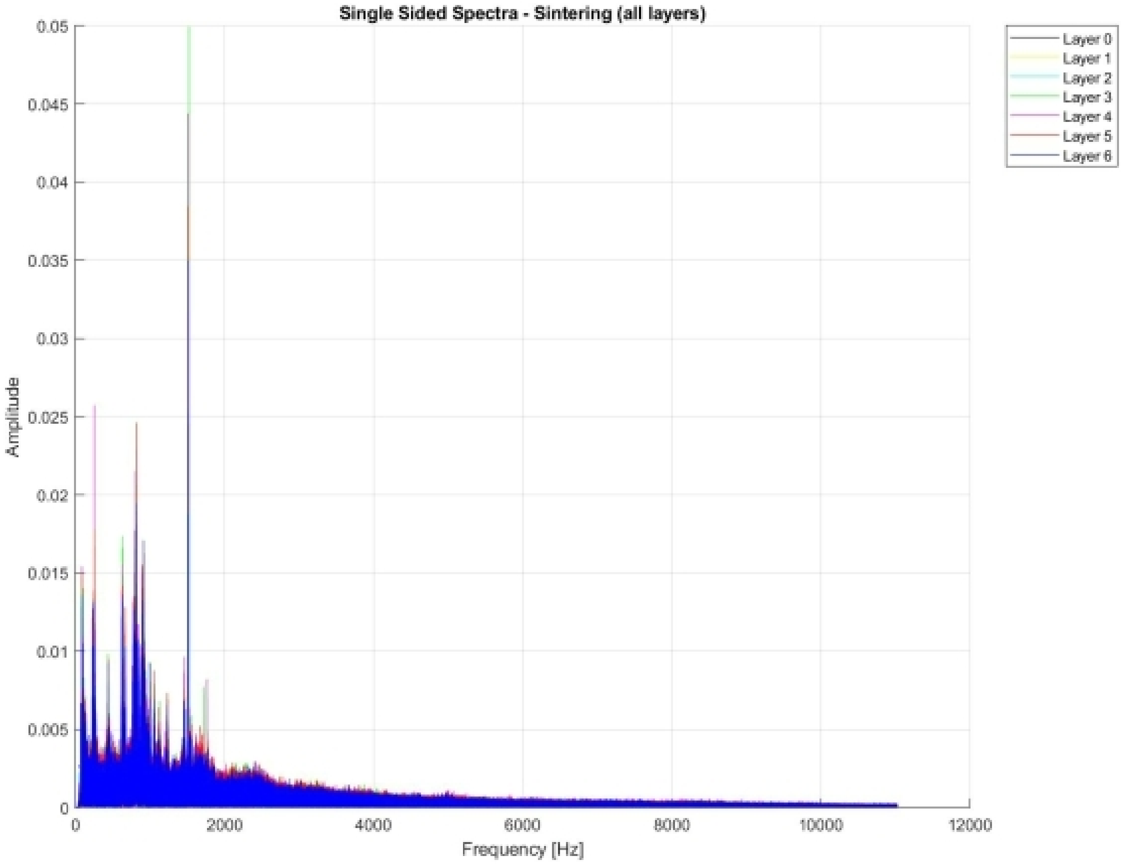
ProX 200 Modification, Spectral & Microphone

3D SYSTEMS

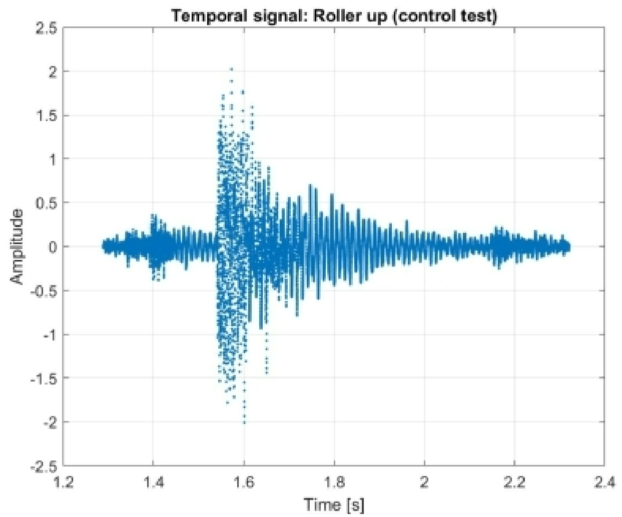
PennState
Applied Research Laboratory

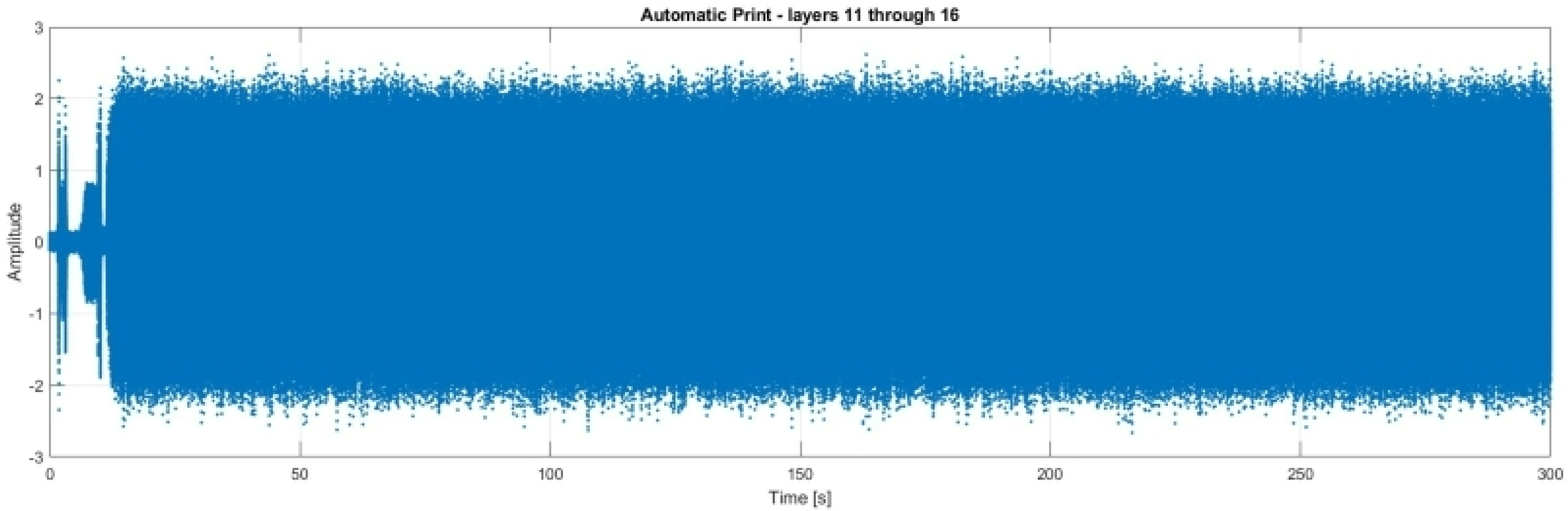
Frequency Spectra of Noise Sources

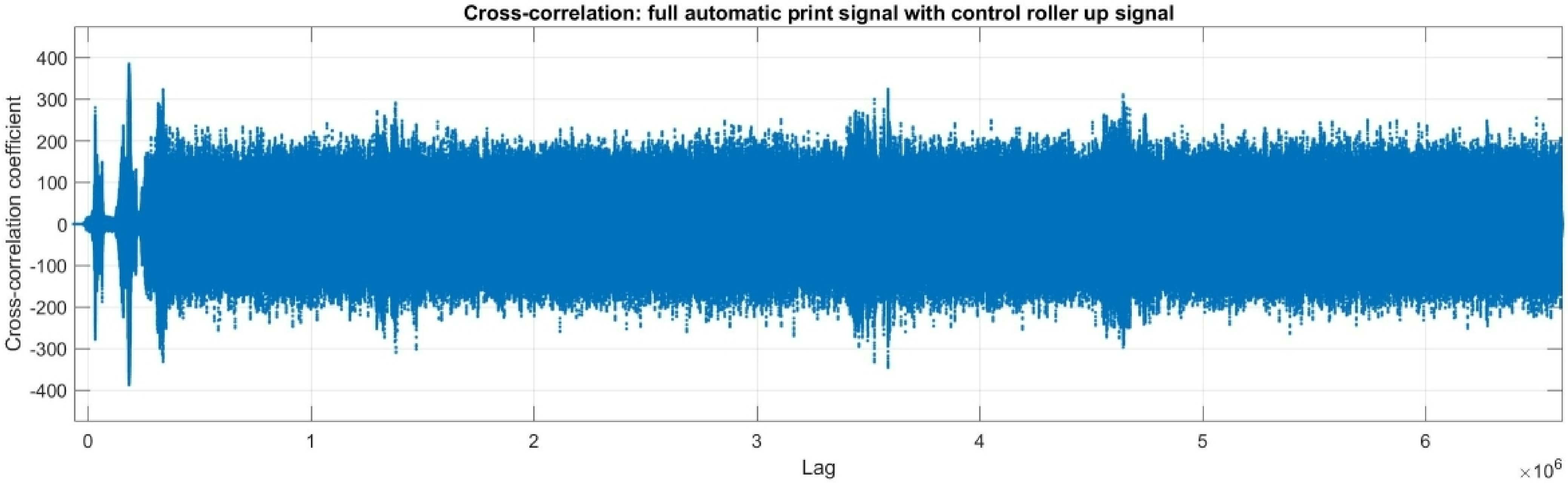




Identifying Noise Sources in a Longer Acoustic Signal







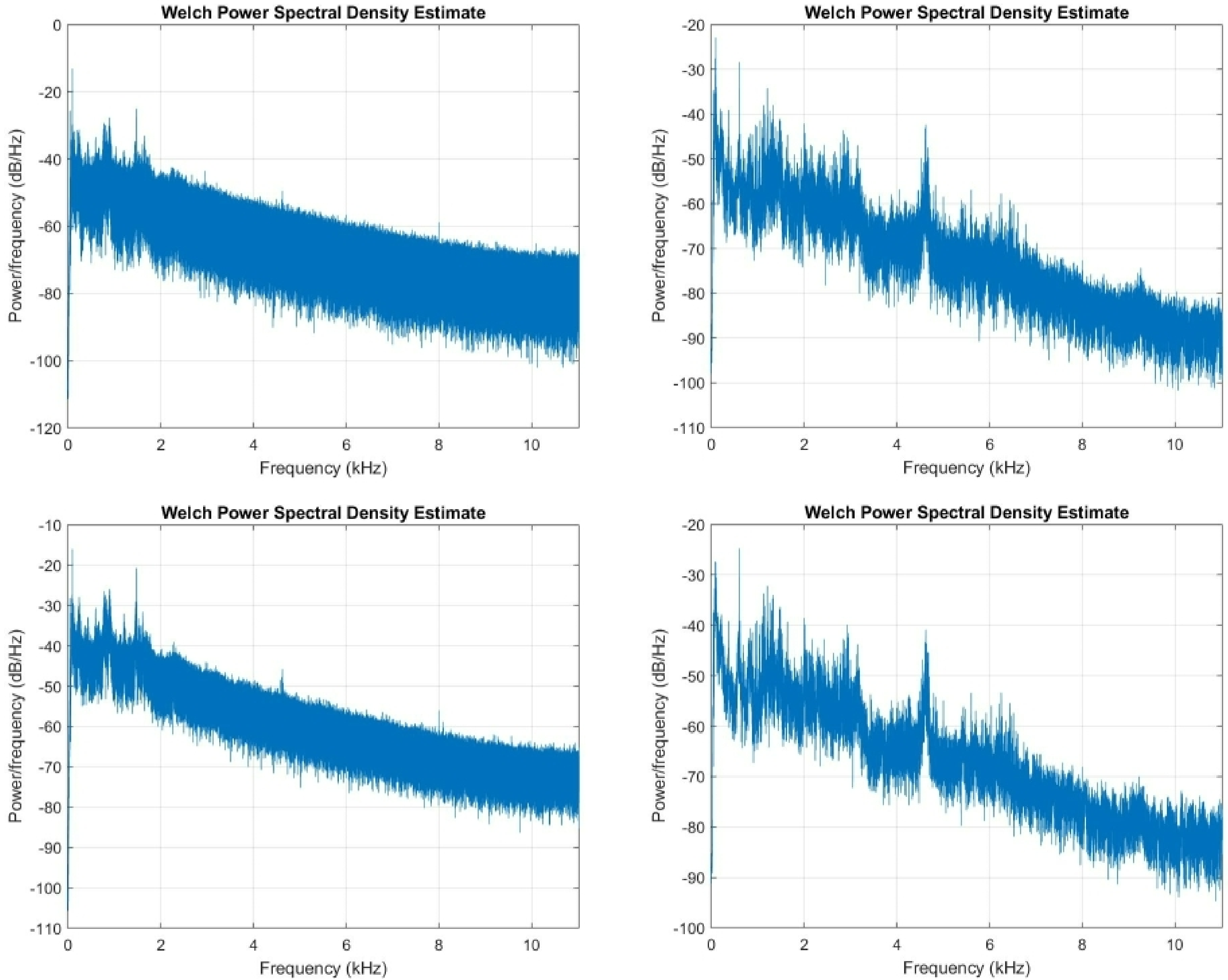
Detecting Build Problems from Acoustic Samples

Power spectral density estimates:

- MATLAB pwelch function using a Hamming window

Left images represent acoustic data collected during several layers of an automatic print

Right images represent acoustic data collected with additional powder deposited to simulate a rough surface



Grammar-based Anomaly Detection in Time-Series Data

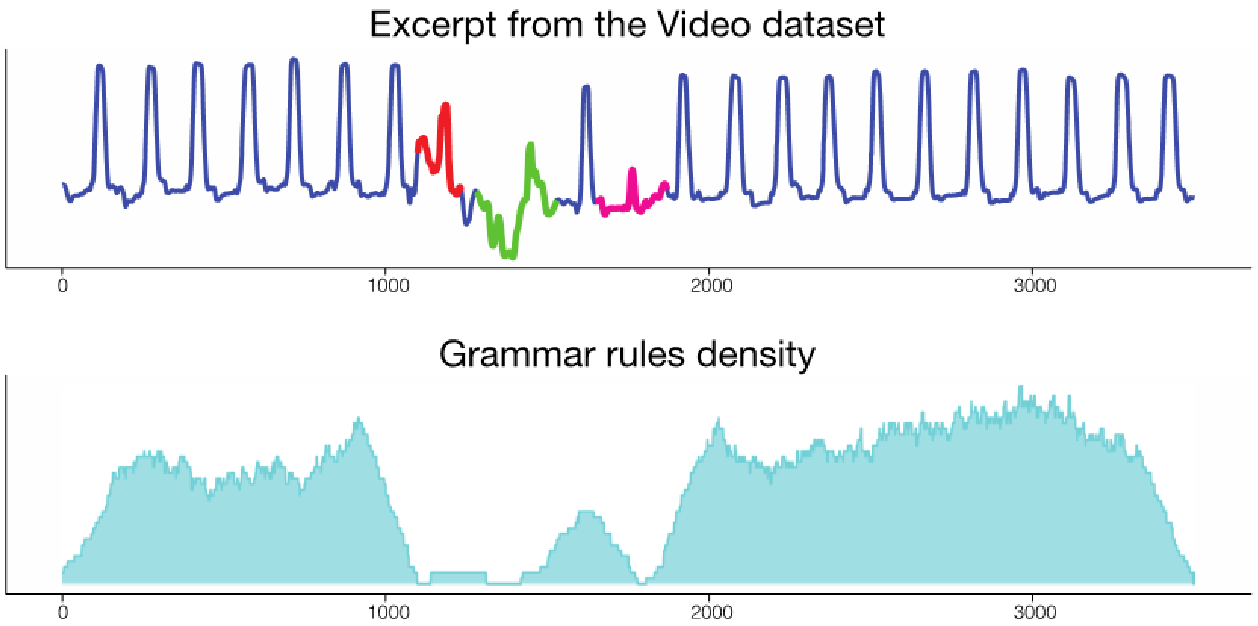
A time series is approximated by a **discrete string of symbols** using the Symbolic Aggregate approXimation (SAX) algorithm.

After discretizing the input time series into a string of symbols, a context-free **grammar is induced** using a grammar compression algorithm.

The obtained set of grammar rules is used to construct a **rule density curve**. The value of the curve at each time point is the count of grammar rules that cover that point.

The minima of the rule density curve indicate locations of most rare/unusual substrings which are **candidate anomalies**.

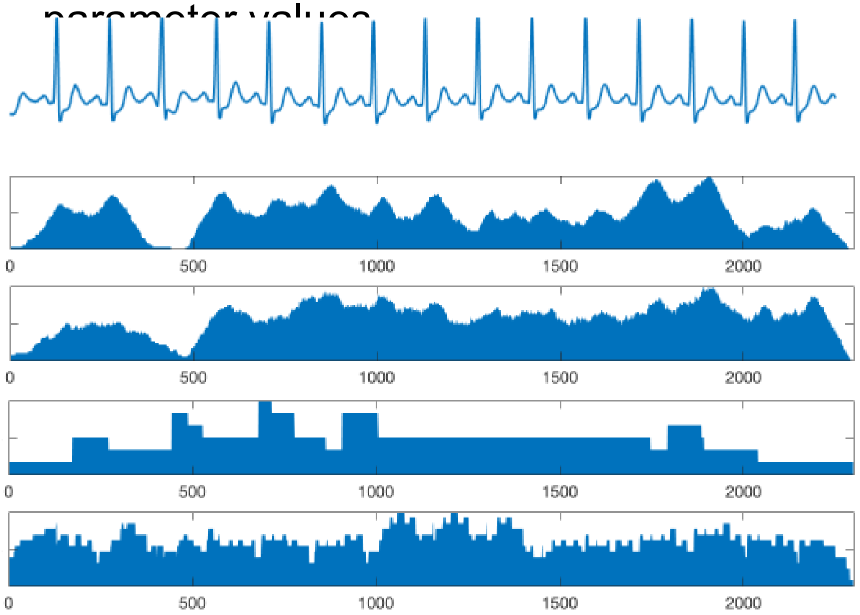
Excerpt from a video dataset (converted into a time series) with three anomalous subsequences highlighted



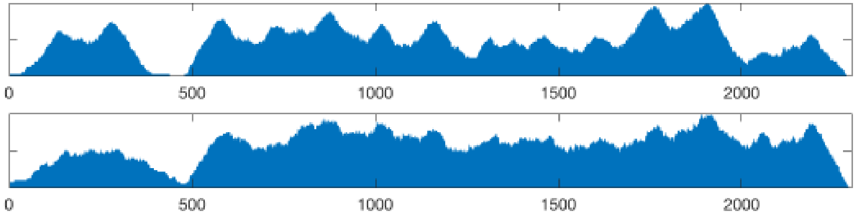
Ensemble Grammar Induction (EGI) method

We combine ensemble learning with grammar induction to achieve robust and efficient anomaly detection in time series data

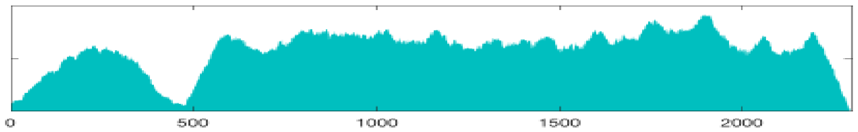
Generate a set of rule density curves with different combinations of parameter values



Remove low-quality curves that have small standard deviations (low prediction power)



Combine all the remaining high-quality curves by computing their median



Use the resulting ensemble rule density curve to detect candidate anomalies

Y. Gao, J. Lin, and C. Brif, "Ensemble grammar induction for detecting anomalies in time series," in *Proceedings of the 23rd International Conference on Extending Database Technology (EDBT 2020)*, pp. 85–96.

Detecting anomalies on extra-long scale

In some applications, grammar induction can have a limited effectiveness in detecting long scale anomalies.

This problem can be addresses by leveraging a new variable-length motif discovery algorithm, **Hierarchy based Motif Enumeration (HIME)**.

Motifs are recurrent patterns in a time series, and motif discovery can be used as a key step in anomaly detection — **subsequences that contain least number of frequent motifs are anomaly candidates**.

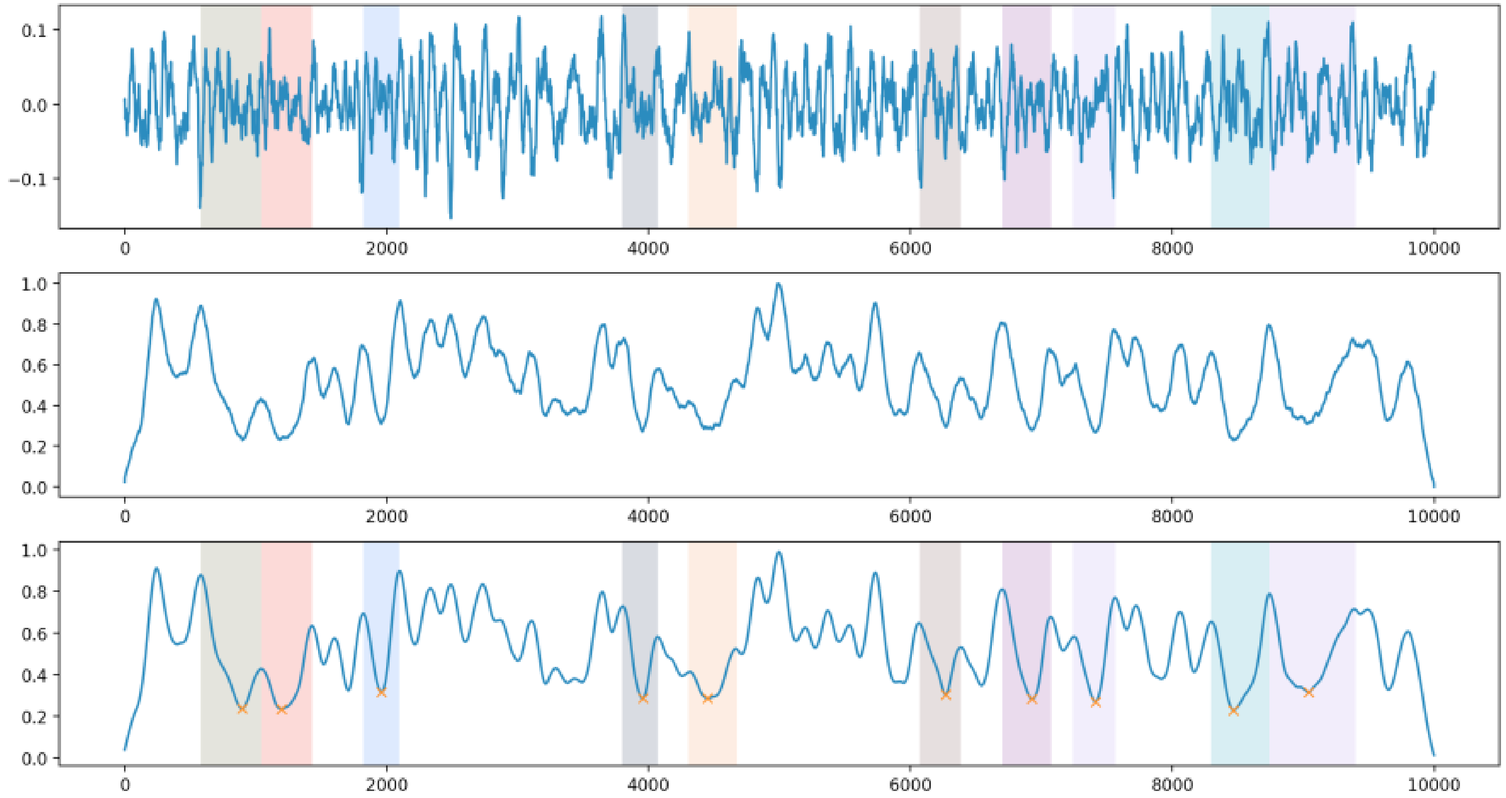
Outline of the approach:

1. Use HIME to identify a set of motifs in the time series.
2. Use Mueen’s Algorithm for Similarity Search (MASS) to identify all instances of each motif contained in the time series.
3. For each motif, compute the correlations between each instance subsequence and the seed subsequence.
4. Compute a motif correlation density curve (MCDC). The value of the curve at each time point is the sum of all instance-seed correlations that cover that point.
5. The minima of the MCDC indicate locations of candidate anomalies, in the same manner as the minima of the rule density curve do in the grammar induction method.

Motif-based approach – Example 1

An example of motif-based anomaly detection in a time series obtained from an acoustic recording of the LPBF process.

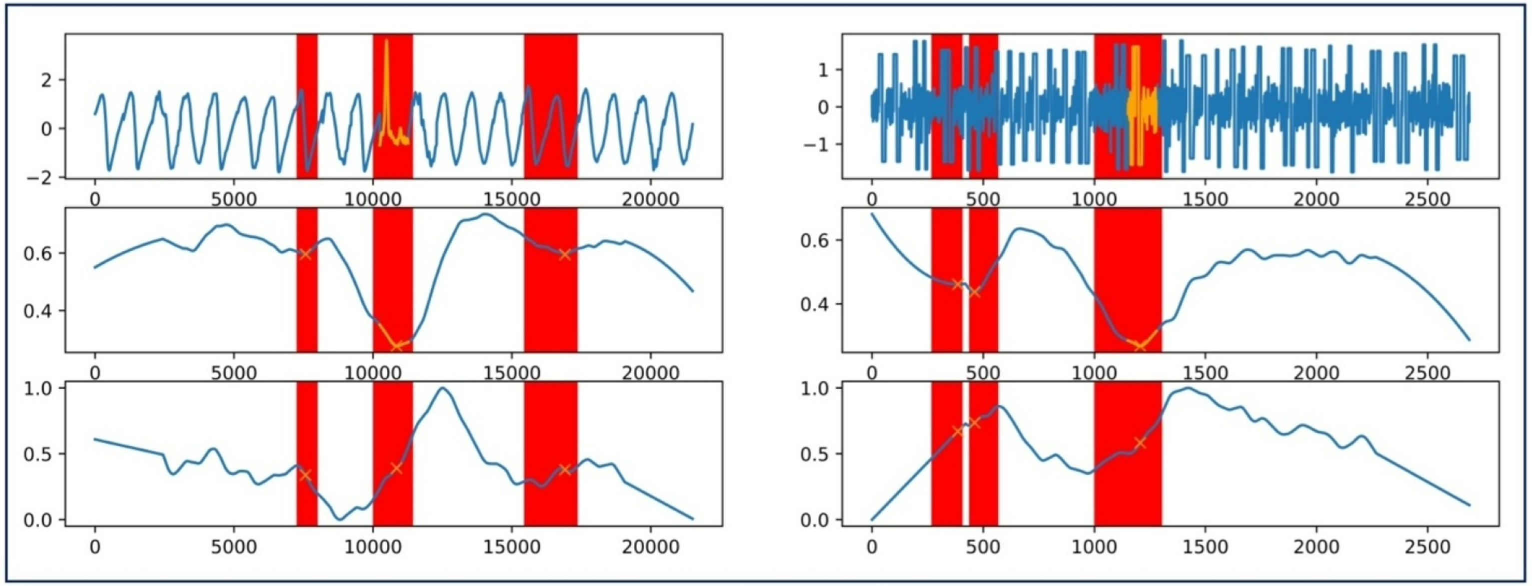
- Top panel: Acoustic time series
- Middle panel: Computed MCDC
- Bottom panel: MCDC with minima indicated by an orange 'X', and anomaly candidate segments indicated by color (anomaly length is estimated by analyzing the slope of the MCDC)



Motif-based approach – Example 2

An example of motif-based anomaly detection using two datasets in the UCR open-source collection. The left example contains an anomaly easily visibly distinguishable, while the right contains an anomaly not visibly different from normal data.

- Top panel: Input time series (the true anomaly highlighted in orange, candidate anomalies highlighted in red)
- Middle panel: Computed MCDC with minima indicated by an orange 'X', and anomaly candidate segment indicated by orange highlight.
- Bottom panel: MCDC derivative (normalized) used to determine the anomaly length.



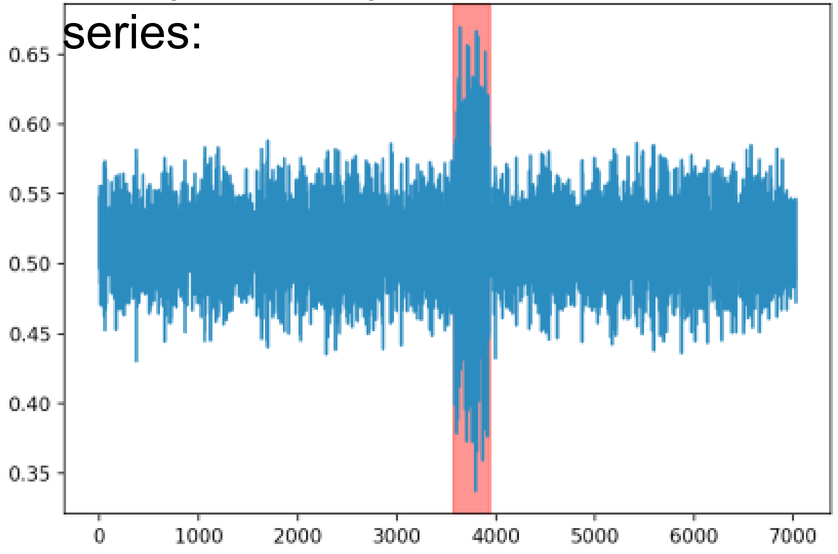
Analysis of Acoustic LPBF data

Work in progress: we are now investigating the use of EGI and MCDC for anomaly detection in acoustic LPBF data

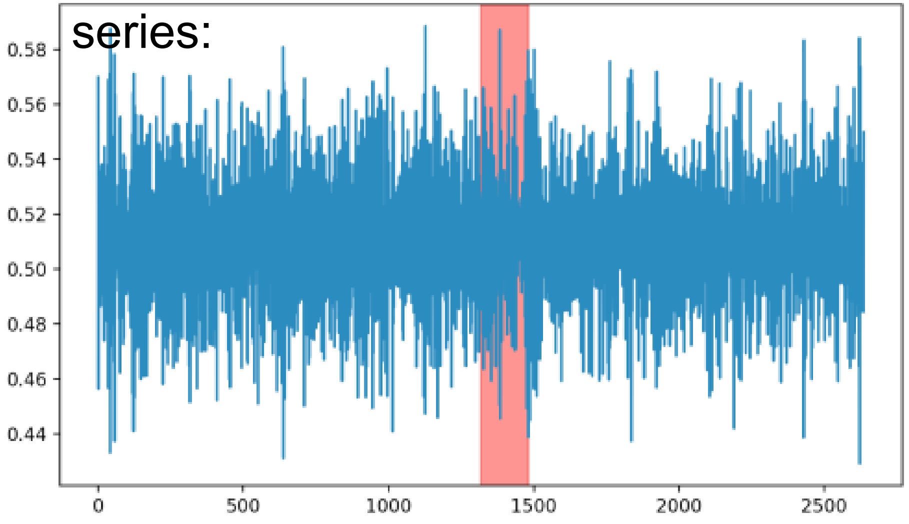
To test the performance, we generated 1000 time series with randomly inserted anomalies, divided into 5 groups:

- Group 1: Sintering signal with anomaly from a random YouTube sound clip
- Group 2: Sintering signal with anomaly from machine idle noise
- Group 3: Sintering signal with anomaly from machine layering sound
- Group 4: Sintering signal with anomaly from a sintering signal from a different run
- Group 5: Sintering signal with anomaly from a time-reversed segment from the same run

Group 1 example time series:



Group 5 example time series:

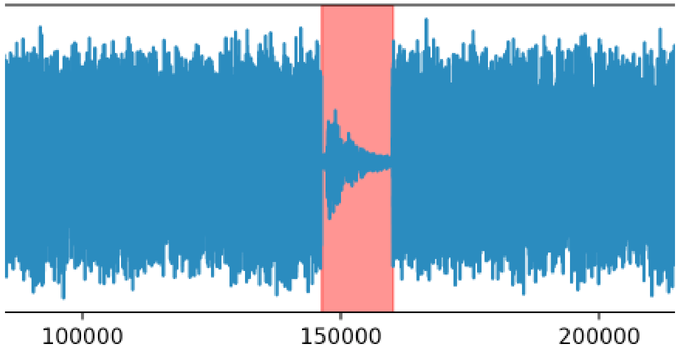


*Anomaly segments highlighted in red

Filtering Acoustic Data

Due to large data size (10^6 to 10^8 data points) and high levels of noise in acoustic data, we use pre-processing (filtering and downsampling)

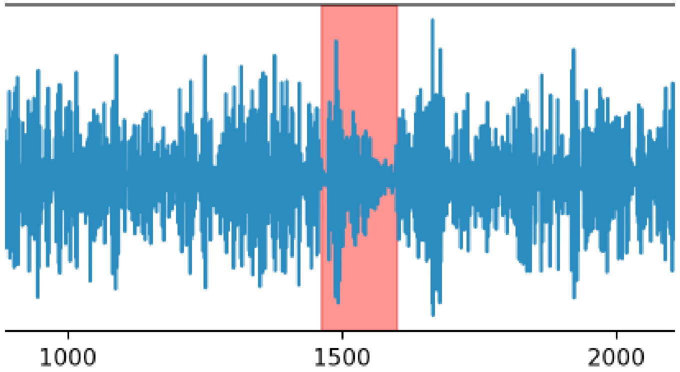
Normal time series before filtering



Filtering using Savitzky-Golay with the following parameters:

- Window Size: 101
- Polynomial Order: 5

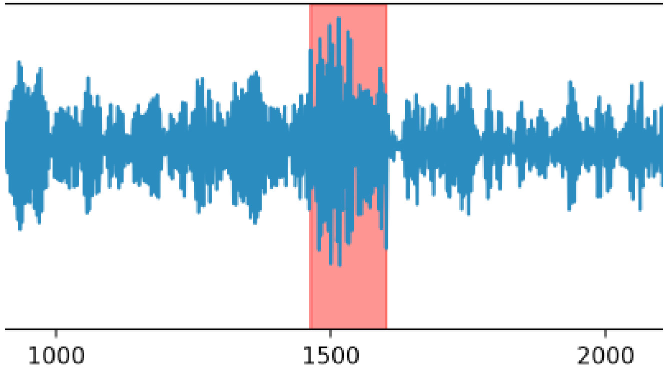
Downsampling using PAA with a window size of 100



Filtering using a digital Butterworth low-pass filter design with the following parameters:

- Wn (Critical Frequency): 0.005
- Polynomial Order: 15

Downsampling using a 30 point FIR filter with Hamming window with downsampling factor (q) = 100



*Anomaly segment highlighted

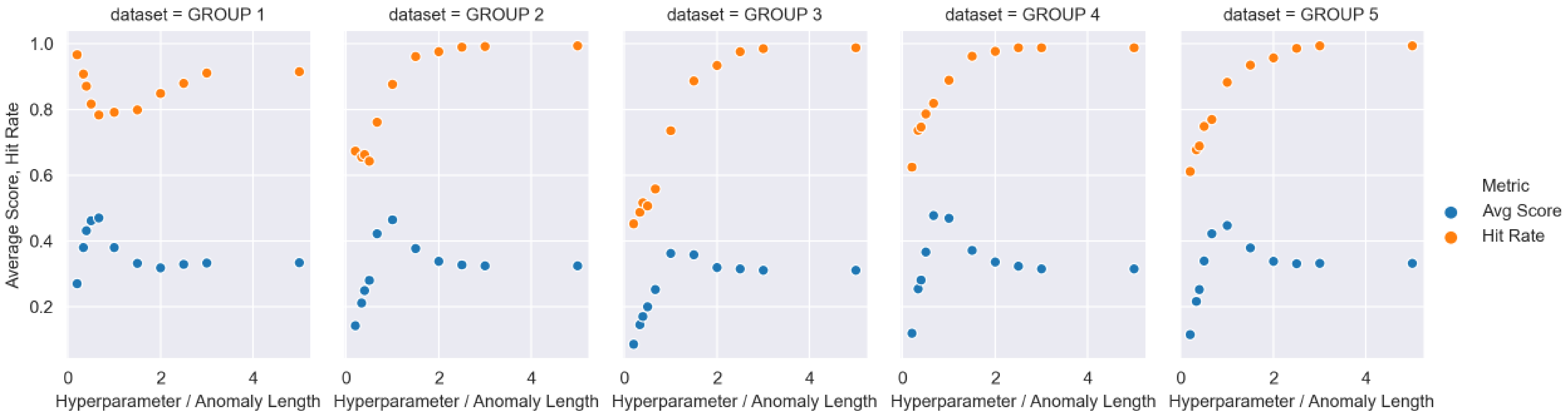
Results for EGI-based Anomaly Detection in Acoustic Data

Performance metrics:

- Score — a measure of overlap between the ground truth anomaly and the candidate anomaly found by EGI
- Hit Rate — the fraction of candidate anomalies with non-zero score
- The average Score and Hit Rate are computed over a set of 200 time series in each group

Dependence on hyperparameter value:

- EGI performance depends on the value of a hyperparameter — sliding window size
- Figure shows the performance metrics values obtained for EGI as the hyperparameter value varies between one fifth and five times the actual anomaly length



*Data pre-processed using the Savitzky-Golay filter

Future Work and Applications

Ongoing and future work

- Continue investigations of cross-correlation to identify noise sources in a longer automatic print (ongoing)
- Development of manual filters for common noise sources (ongoing)
- Analyze acoustic data for failure modes including rough surface and holes, gather additional data as needed
- Implement simultaneous data collection of laser motion data using ARCS (Archive, Research, Control, Synchronization) system
- Testing of MCDC algorithm performance with known datasets (ongoing)
- Applying MCDC algorithm to acoustic datasets where anomaly information is unknown (ongoing)

Applications

- Monitoring an additive manufacturing process *in situ* to identify abnormal noises that could indicate a problem with the build
- Joint data collection and monitoring with multiple methods for better identification of defects and build issues, both *in situ* and post-processing

Questions?

Elaine Rhoades

Sandia National Labs elrhoad@sandia.gov

Georgia Institute of Technology erhoades3@gatech.edu