ICAAI 2019

Putting together Wavelet-based Scaleograms and CNN for Anomaly Detection in Nuclear Reactors

Thanos Tagaris, George Ioannou, Maria Sdraka,
Georgios Alexandridis and Andreas Stafylopatis

Abstract

A critical issue for the safe operation of nuclear power plants is to quickly and accurately detect possible anomalies and perturbations in the reactor. Defects in operation are principally identified through changes in the neutron flux, as captured by detectors placed at various points inside and outside of the core. This work presents a novel technique for anomaly detection on nuclear reactor signals through the combined use of wavelet-based analysis and convolutional neural networks. In essence, the wavelet transform is applied to the signals and the corresponding scaleograms are produced, which are subsequently used to train a convolutional neural network that detects possible perturbations in the reactor core. The overall methodology is experimentally validated on a set of simulated nuclear reactor signals generated by a well-established relevant tool. The obtained results indicate that the trained network achieves high levels of accuracy in failure detection, while at the same time being robust to noise.

Dataset Description

The dataset has been constructed using the SIMULATE-3K tool. The produced signals are grouped in 4 classes:

- Fuel Assembly Vibrations
- Cluster of Fuel Assemblies synchronously vibrating
- Coolant Flow Oscillations
- Coolant Temperature Oscillations

Data Preprocessing

The preprocessing steps are the following:

- Removing the trend from the signals
- Resampling all signals into the same length
- Cutting the signal into smaller parts for more data and for using them in a cross-validation scheme

Mother Wavelet Selection

The best mother wavelet for the Discrete Wavelet Transform (DWT) was determined by two criteria:

- Maximizing Cross-Correlation:

$$\gamma(X,Y) = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2\sum(Y-\bar{Y})^2}}$$

- Maximizing Energy-to-Entropy:

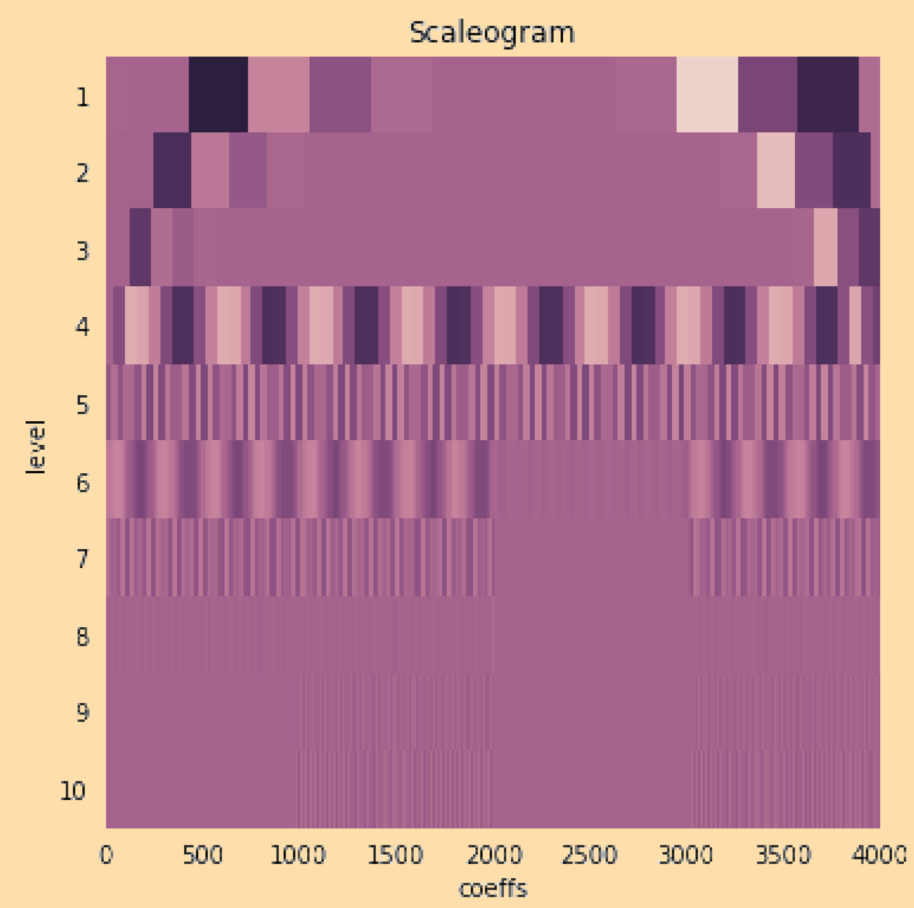
$$Energy\,(s) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} s_i^2}$$

$$Entropy\,(s) = \sum_i \left(s_i^2 \cdot log\,(s_i^2)\right)$$

$$\zeta\,(s) = \frac{Energy\,(s)}{Entropy\,(s)}$$

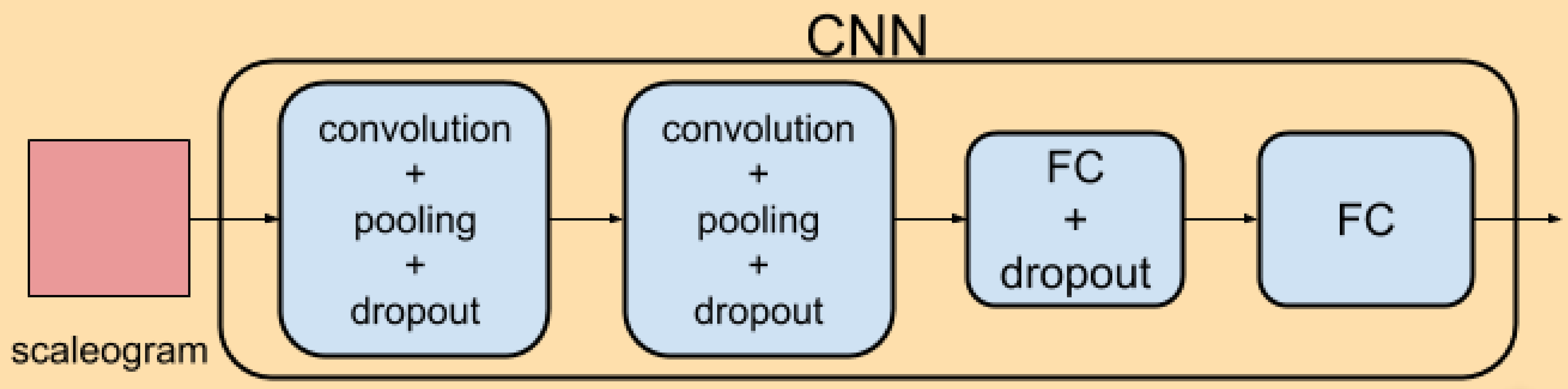
Scaleogram Extraction

After choosing the best mother wavelet, the DWT is applied. Then, the wavelet coefficients are being illustrated through a scaleogram. Scaleograms are a type of two-dimentional heatmap that depicts the spectrum of the DWT frequencies through time. It is similar to a spectrogram and it will be the input of the neural network.



Model architecture

This is the deep model that was used to classify the signals into the given perturbation groups.



Results

Below are presented the results of the k-fold cross-validation scheme. The k hyperparameter matches the number of splits of each signal. The metric used is the mean accuracy of all folds.

k	In-core	Ex-core
2	98.04%	83.33%
4	99.63%	83.44%
8	99.85%	93.88%

From the results we can derive the following conclusions:

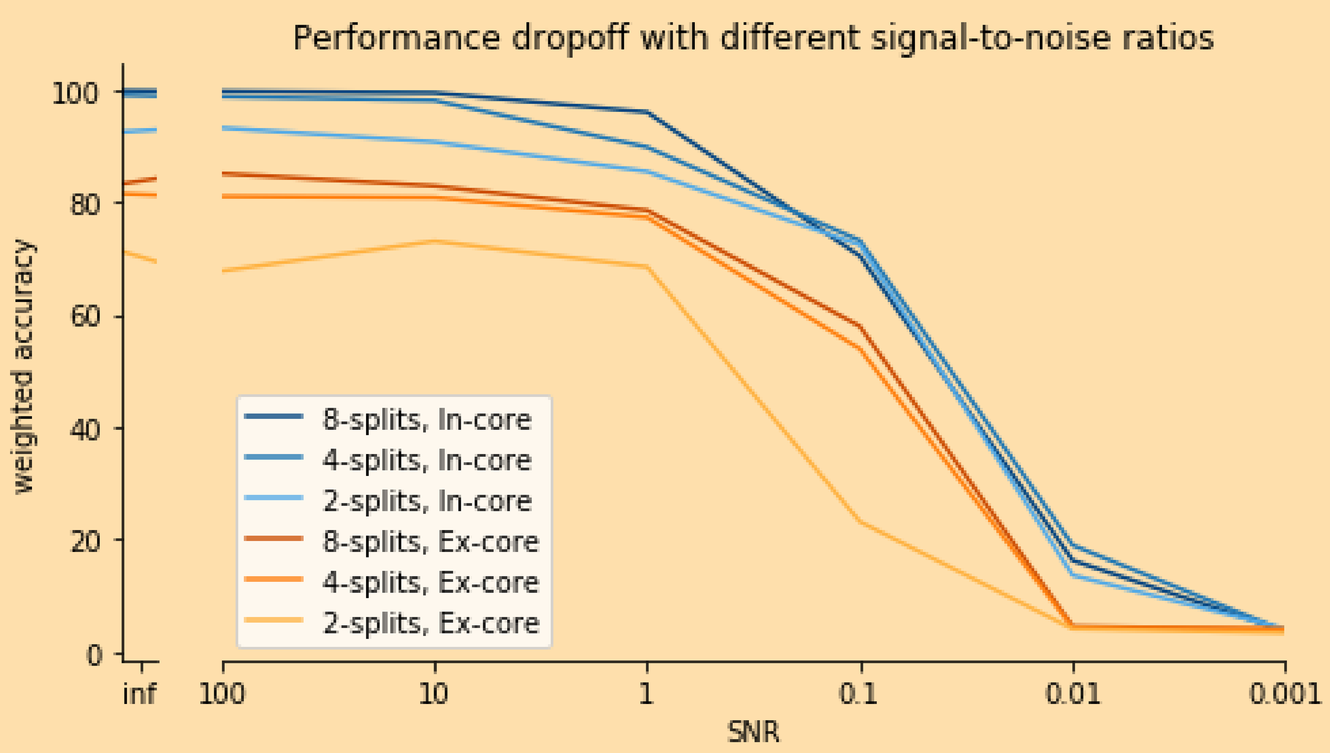
- The overall methodology seems to successfully differentiate between the different perturbations.
- The more splits lead to more training data, which leads to better performance
- In-core sensors produce better classification results, but they are harder to use.

Noise Analysis

To prove the robustness of the method, noise analysis was performed. Noise with different SNR values was added to the signals.

$$SNR = \frac{P_{signal}}{P_{noise}}$$

On the right, the figure illustrates the accuracy of the model for the different SNR values. With $SNR < 10$ the performance starts to deteriorate. In-core signals again exhibit better performance than ex-core ones.



Acknowledgement

This project has received funding from the Euratom research and training programme 2014-2018 under grant agreement No 754316.
We express our gratitude to the Paul Scherrer Institute (PSI), Switzerland, for supplying the data used in our experiments, within the framework of the aforementioned project.