

CORTEX

Core monitoring techniques and
experimental validation and demonstration

Deep Learning-based Anomaly Detection in Nuclear Reactor Cores

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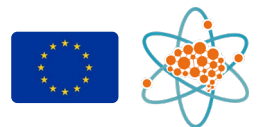
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This project has received funding from the Euratom research and training programme 2014-2018 under grant agreement No 754316. The content in this presentation reflects only the views of the authors. The European Commission is not responsible for any use that may be made of the information it contains.

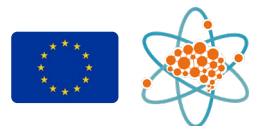
Overview

- The introduction of a deep learning methodology for the classification of different perturbation types and their position in the reactor core, using convolutional neural networks
- The performance of a complementary robustness analysis to assess the system's performance on noisy or missing data
- The assessment of the system's functionality on plant measurements obtained from the Gösgen nuclear power plant in Switzerland



Noise analysis

- Assess the condition of the reactor core using noise diagnostics
 - Measure the fluctuation of neutron flux around a mean value using in-core & ex-core detectors
- Type & number of perturbations occurring in the core is usually unknown
- Modelling techniques allow for the simulation of perturbations in the core
 - Estimate the induced neutron flux in the core for known, realistic perturbations
- The deep learning architecture learns the patterns of the simulated perturbations...
- ... and tries to determine whether they occur in actual plant measurements

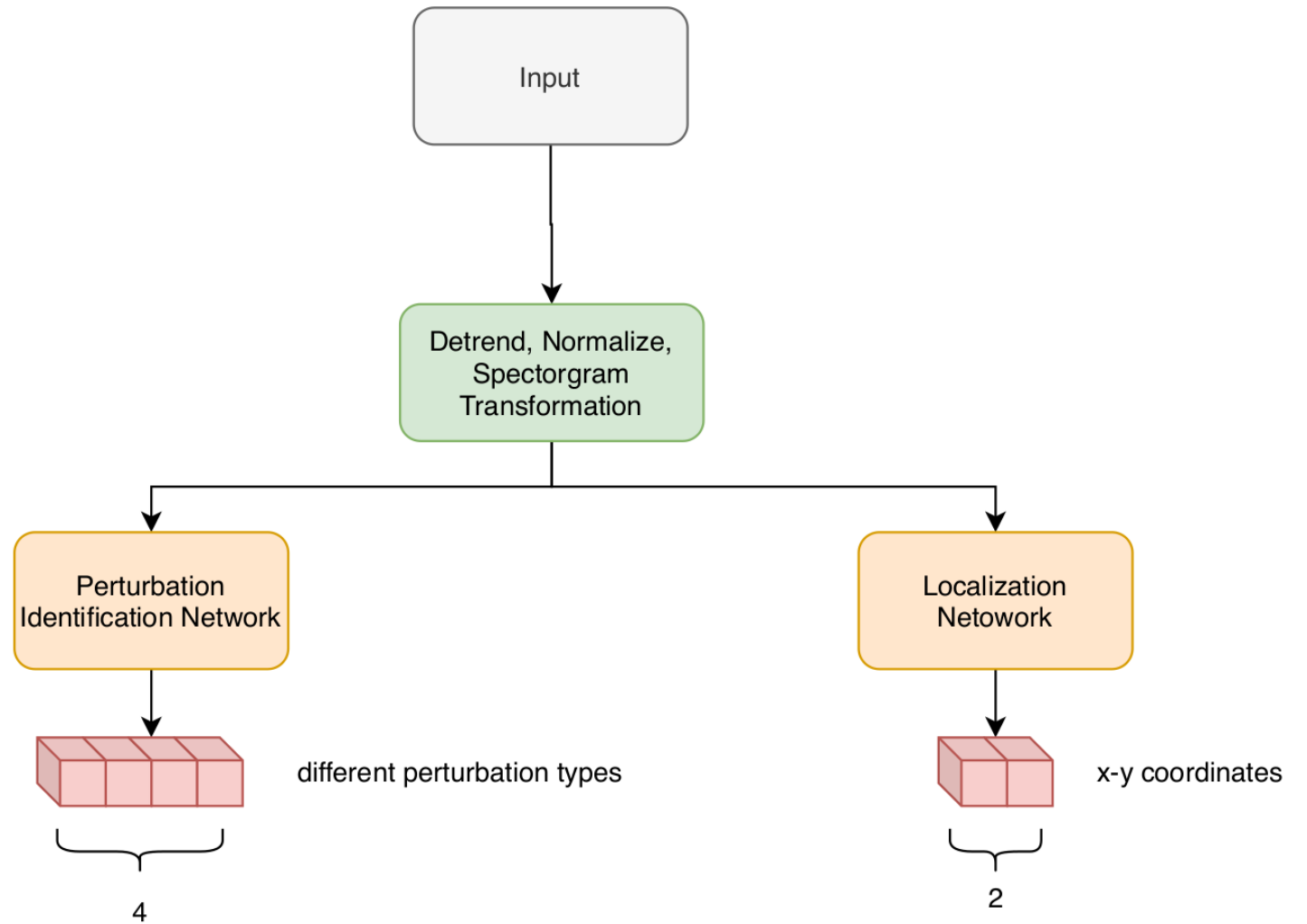


Simulated measurements

- Performed for a Swiss pre-KONVOI pressurized water reactor
 - 3-loop reactor, 177 fuel assemblies
- Neutron noise simulations based on the CASMO-5 SIMULATE-3 code system, coupled with the SIMULATE-3K transient nodal code
- Type of perturbations
 - Individual fuel assembly vibrations
 - Cantilevered, C-shape and S-shaped modes
 - Inlet coolant temperature fluctuations
 - Inlet coolant flow fluctuations
 - ... and their combinations

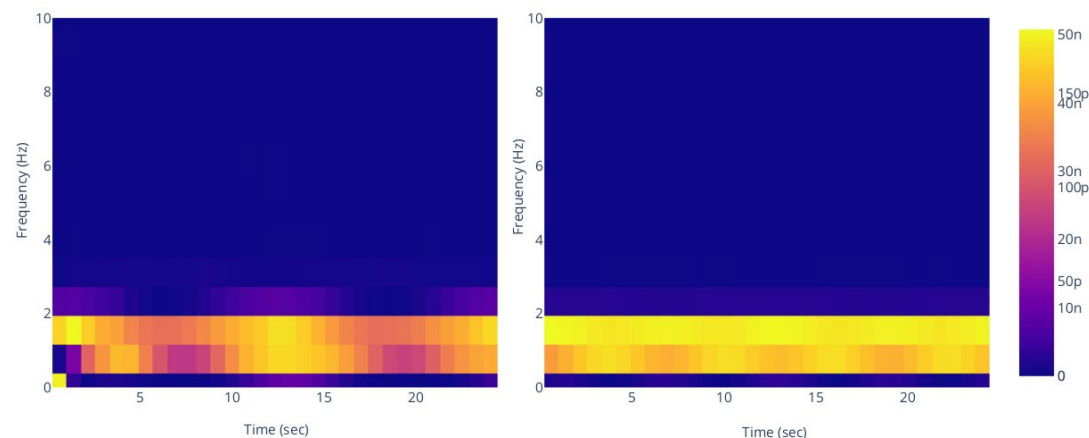


The proposed architecture at a glance

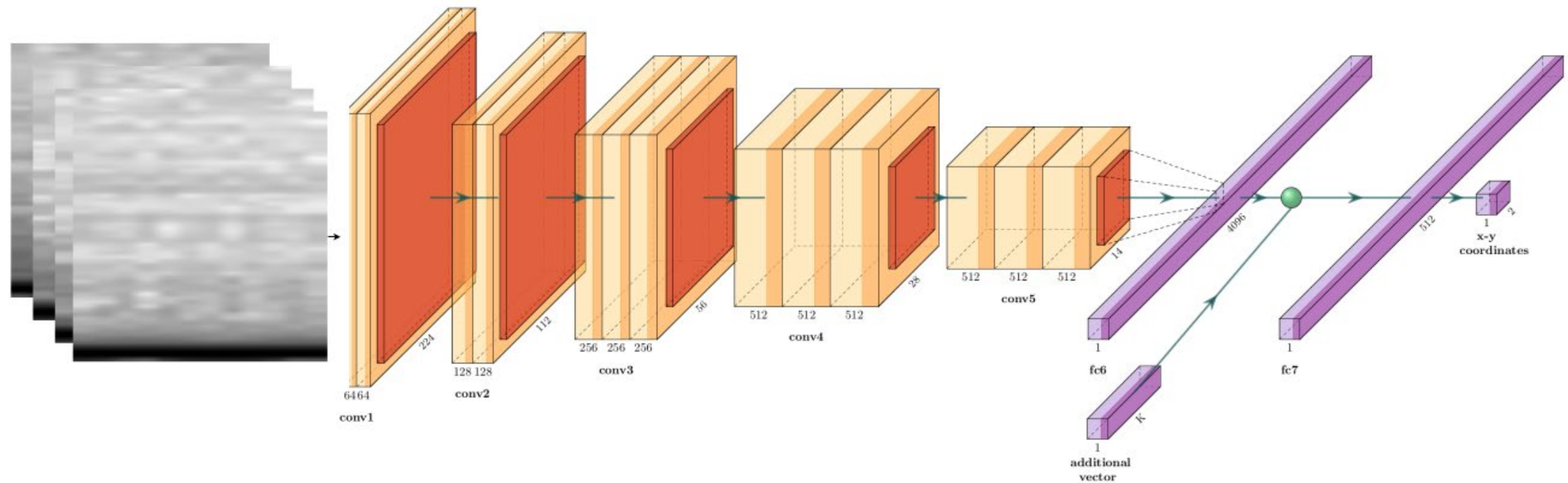


System input

- Input is a transformed version of the initial detector signal
- Input is detrended and normalized
- Time domain signals are transformed into scaleograms, based on the wavelet transform



ResNet architecture (identification & localization networks)



Identification task results

F1-score of the perturbation identification network for varying SNR ratios

Perturbation type	SNR=10	SNR=1	SNR=0.1	SNR=0.01
FA vibration	1.00	1.00	0.99	0.17
Inlet temperature fluctuation	1.00	0.99	0.53	0.30
Inlet flow fluctuation	1.00	1.00	0.62	0.09
Cluster vibration & thermohydraulical fluctuation	0.99	0.99	0.66	0.30



Localization task results

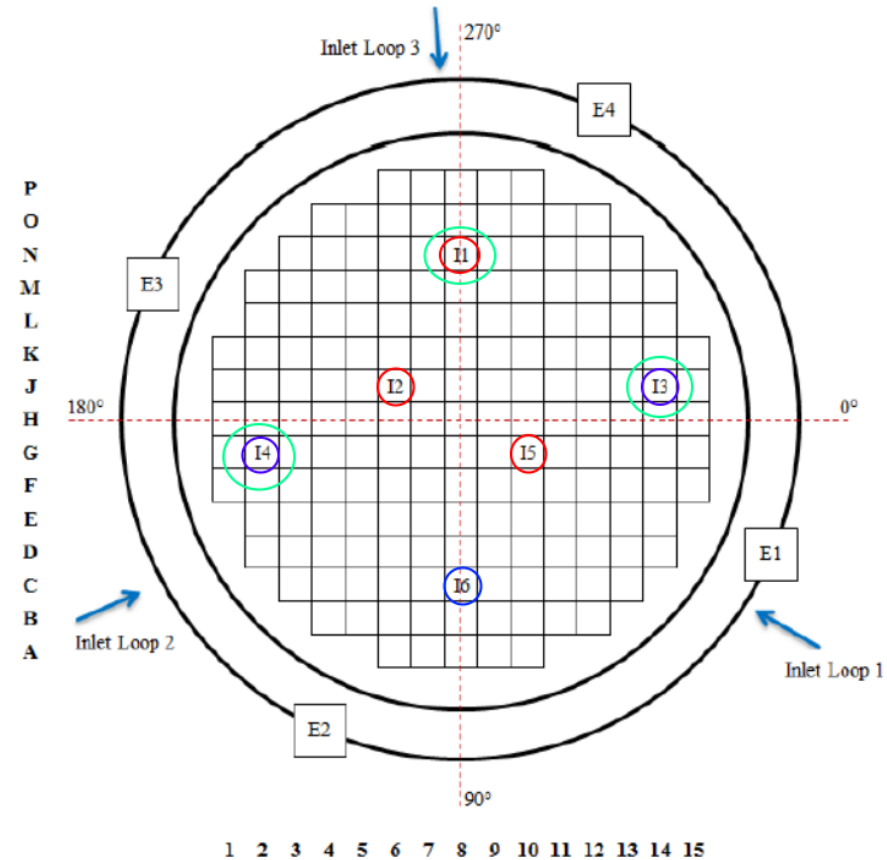
Only for the fuel
assembly vibration case

Prediction accuracy of the localization network

Prediction proximity	Proportion of the test set
exact	0.73
1 difference	0.21
> 1 difference	0.06

Robustness Analysis: faulty detectors

- Assess the distinguishing capability of the models, given partial information about grid condition
- Create subsets of functional in-core & ex-core detectors

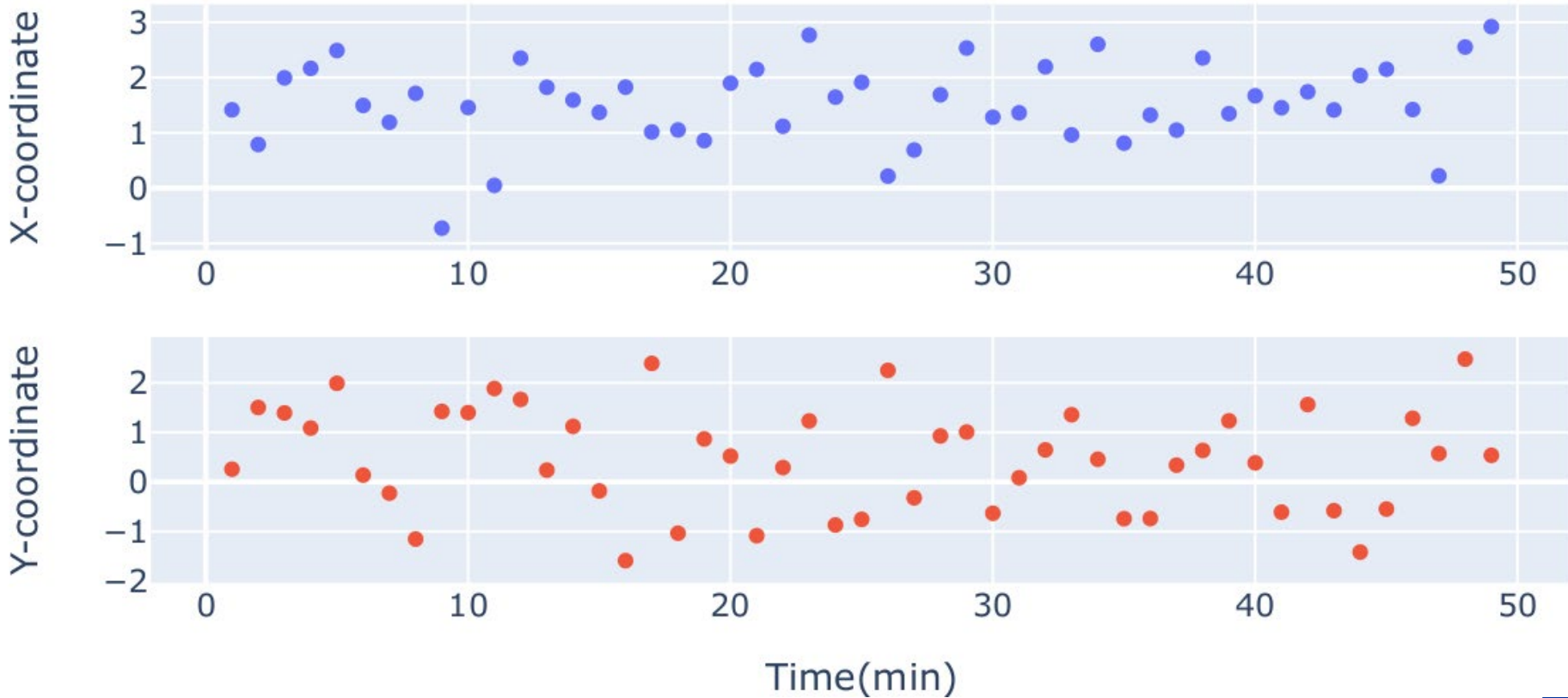


Prediction accuracy of the localization network for different subsets of functional detector signals

Prediction proximity	Functional subsets of detectors					
	I_1, I_2, I_5	I_1, I_2, I_5 + ex-core	I_3, I_4, I_6	I_3, I_4, I_6 + ex-core	I_1, I_3, I_4	I_1, I_3, I_4 + ex-core
exact	0.52	0.58	0.48	0.65	0.43	0.66
1 difference	0.31	0.32	0.32	0.26	0.34	0.22
2 difference	0.11	0.07	0.13	0.07	0.15	0.09
> 2 difference	0.06	0.03	0.07	0.02	0.08	0.03



Preliminary comparison with plant measurements



Thank you! Any questions?

