CORTEX
Core monitoring techniques and experimental validation and demonstration

Deep learning: 3D convolutional and recurrent neural networks in reactor perturbations unfolding and anomaly detection

CORTEX Workshop

Advanced signal processing methods and learning methodologies applied to the monitoring of NPP reactor conditions

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Introduction

Purpose:

To propose a novel framework for the analysis of perturbations in both the time- and frequency- domain

Identification of type and source of such perturbations is fundamental for monitoring reactor cores and guarantee safety while running at nominal conditions

Data Generation

Frequency Domain Related

Simulation conducted using CORE-SIM tool using a Pressurized Water Reactor (PWR) with:

- Radial core 15 x 15 fuel assemblies
- Volumetric mesh 32 x 32 x 26
- Dirac's like perturbations at 0.1*Hz*, 1*Hz* and 10 *Hz*
- Green's function as the reactor transfer function

Data Generation

CORE-SIM output

- Fast and thermal response to applied perturbation
- A complex signal distributed in a 3D array 32 x 32 x 26

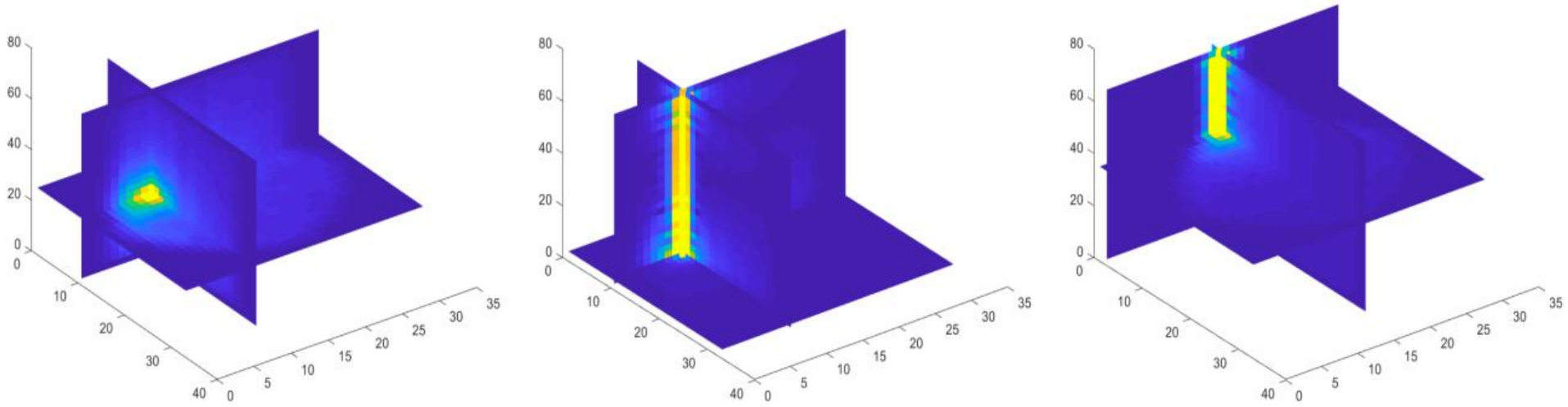
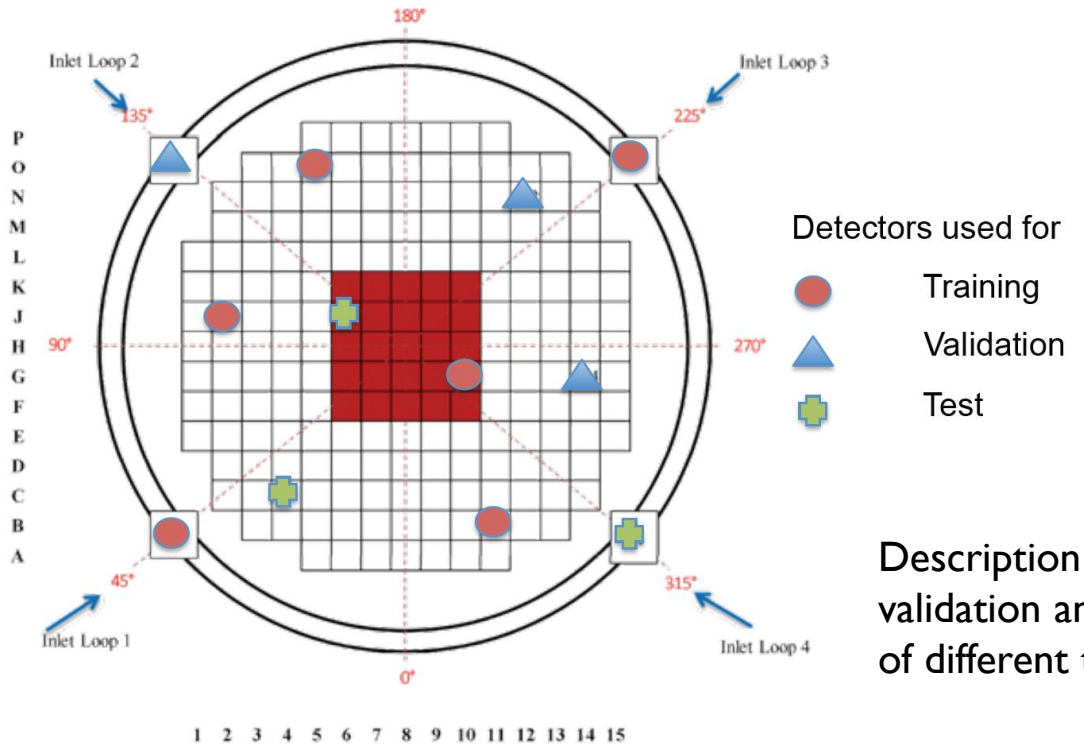


Fig. 1. Examples of induced neutron noise types. From Left to Right, the responses to *Localised*, *Propagating* type 1 and 2 perturbations are illustrated.

Data Generation

Time-domain data:

Simulate-3K (S3K) was utilised to model fuel assemblies cluster vibrations, including fluctuations in thermal-hydraulic parameters between the coolant loops, on a model of the four loop Westinghouse PWR mixed core,



4 ex-core detectors at 2 levels
8 in-core detectors at 6 levels
5 x 5 FAs cluster

Description of detector locations for the signals utilised in training, validation and testing of the deep LSTM network model, in the classification of different types and combinations of Time domain perturbations.

Scenarios

Table: Synchronised vibration of a 5×5 fuel assemblies central cluster.

Scenario	Perturbation	Frequency	Amplitude	ID
1	5×5 cluster FAs	WN	1 mm	1 0 0 0
	5×5 cluster FAs	WN	0.5 mm	1 0 0 0
2	5×5 cluster FAs	1 Hz	1 mm	0 1 0 0
	5×5 cluster FAs	1 Hz	0.5 mm	0 1 0 0

Table: Synchronised perturbation of coolant thermal-hydraulic parameters.

Scenario	Perturbation	Frequency	Amplitude	ID
3	temperature	random	$\pm 1^{\circ} C$	0 0 1 0
4	flow	random	$\pm 1\%$	0 0 0 1

Scenarios

Table: Combination of synchronised vibration of a 5×5 fuel assemblies central cluster and synchronised perturbation of coolant thermal-hydraulic parameters.

Scenario	Combined Perturbations	ID
5	Temperature (5) & flow (6)	0 0 1 1
6	5×5 FA (2) & temperature (5)	1 0 1 0
7	5×5 FA (1) & temperature (5)	1 0 1 0
8	5×5 FA (4) & temperature (5)	0 1 1 0
9	5×5 FA (3) & temperature (5)	0 1 1 0
10	5×5 FA (2) & flow (6)	1 0 0 1
11	5×5 FA (1) & flow (6)	1 0 0 1
12	5×5 FA (4) & flow (6)	0 1 0 1
13	5×5 FA (3) & flow (6)	0 1 0 1

Proposed Approach

Frequency Domain Related

We address the unfolding problem as:

- Classification - perturbation type
- Regression - perturbation source location

Time Domain Related

We address the problem as:

- Classification - scenario ID

Proposed Approach

Analysed the frequency domain data in its volumetric form and proposed:

3D-CNN:

1. To unfold neutron noise signals up to the original signal resolution (regression problem).
2. To recognise perturbation type, e.g. travelling, localised and combination of them (classification problem).

We analysed the time domain data and proposed:

LSTM network:

To recognise what scenario has been simulated (classification problem). During the prediction phase , the network uses 100 time steps (i.e. 1s) of a signal from a single sensor.

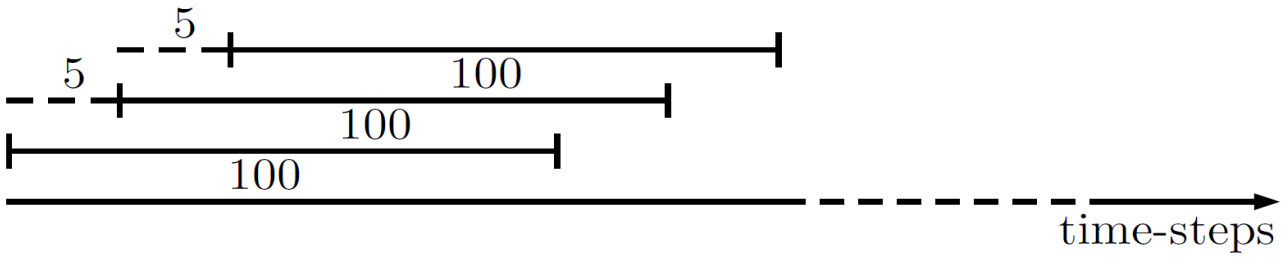


Fig. 3. Signal sampling. Signal windows of 100 time-steps were sampled using sliding windows of stride 5 time-steps

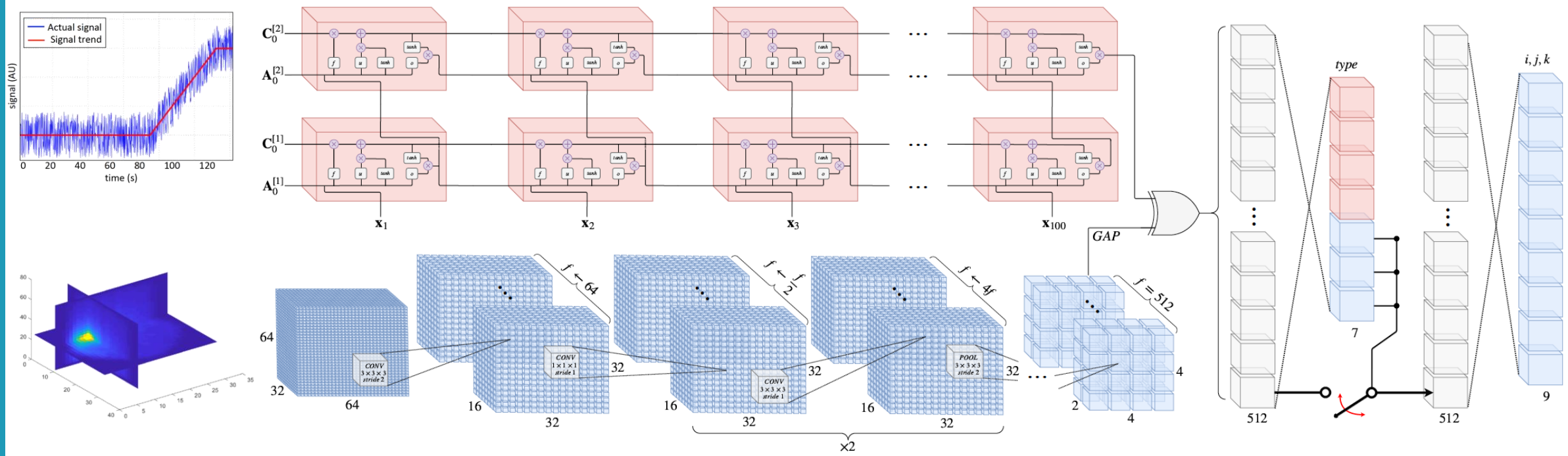
Proposed Approach

The problem of recognising which scenario a signal is representative of was tackled as a multi-label classification task. 512 dimensional LSTM representations were fully connected to four neurons with sigmoid activation functions. During training the negative log-likelihood criterion was minimised:

$$\mathscr{L}(y, \widehat{y}) = -\frac{1}{PN} \sum_{j=1}^{P} \sum_{i=1}^{N} \Big[y_j \log(\widehat{y}_j) + (1 - y_j) \log(1 - \widehat{y}_j) \Big]_i$$

where P is the number of sigmoid units used for the multi-label classification task, and N is the number of samples in a batch.

Proposed Approach



Unified framework for time and frequency domain perturbation type classification and coordinate regression. An LSTM network at the top for time domain signals, and a 3D CNN below for frequency domain signals.

Further analyses..

- Signals in the frequency domain were obscured so that 20% and 5% of the sensors were utilised.
- Signals in the time domain were corrupted by noise at SNR=10 and SNR=5.

Experimental Results

In the frequency domain:

RESULTS OF THE FREQUENCY DOMAIN 3D CNN EXPERIMENTS FOR PERTURBATION TYPE CLASSIFICATION AND LOCALISATION REGRESSION. (*) MARKS COMBINED PERTURBATIONS SCENARIOS.

3D CNN Perturbation Classification & Localisation				
Sensors (%)	Train/Valid/ Test (%)	Classification Accuracy (%)	(i, j, k) Regression	
			MAE	MSE
20	60/15/25	**99.75±0.09**	**0.2528±0.03**	**0.1347±0.02**
20	25/15/60	99.12±0.17	0.4221±0.05	0.4152±0.07
20	15/25/60	98.62±0.22	0.5886±0.05	0.8174±0.12
5	60/15/25	99.32±0.18	0.326±0.05	0.2086±0.04
5	25/15/60	98.34±0.22	0.4818±0.05	0.6044±0.08
5	15/25/60	97.27±0.54	0.689±0.1	1.0749±0.25
20*	60/15/25	99.82±0.05	0.5602±0.04	1.6036±0.15
20*	25/15/60	99.56±0.07	0.8942±0.04	3.5739±0.16
20*	15/25/60	99.44±0.08	0.9635±0.06	4.2814±0.19
5*	60/15/25	99.47±0.03	0.8809±0.04	3.4424±0.16
5*	25/15/60	98.33±0.24	0.5001±0.04	0.6381±0.08
5*	15/25/60	**97.15±0.15**	**1.9528±0.11**	**11.902±0.66**

In the time domain:

RESULTS OF THE TIME DOMAIN DATA FOR SCENARIO TYPE CLASSIFICATION

LSTM network Scenario Classification				
Noise (SNR)	Train/Valid/ Test (#sensors)	Timesteps (#)	Sensors (#)	Classification Accuracy (%)
no noise	28/14/14	100	1	97.01 ± 0.05
10	28/14/14	100	1	81.16 ± 0.15
5	28/14/14	100	1	77.43 ± 0.25

Future work

- Currently extending the approach to additional scenarios in the time-domain, e.g. FA vibrating in the Y direction as well. Promising results thus far; on par with the results presented previously

- Extract knowledge from both the time- and frequency- domain assuming in simulated data; core-sim and simulate 3K need to model the same reactor

- Define scenarios in real data and adapt the developed techniques to real data

Thank you