Towards a Deep Unified Framework for Nuclear Reactor Perturbation Analysis

CORTEX

Core monitoring techniques and experimental validation and demonstration

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Overview

Introduction

- Nuclear reactors monitoring is crucial
- Neutron flux fluctuates due to induced perturbations
- Neutron flux analysis can help detecting reactor anomalies
- Signal in/ex-core detectors are limited in number
- Neutron flux signals can be in time and frequency domain

The Problem

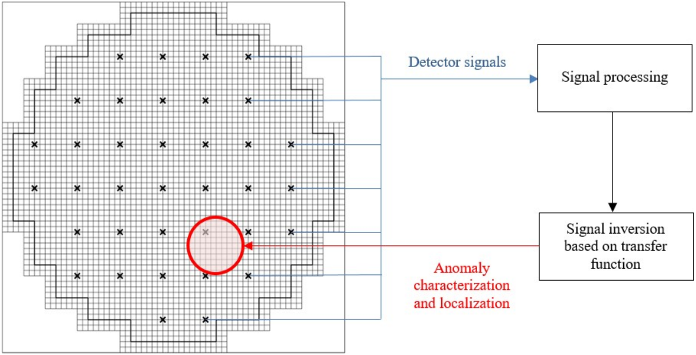


Figure: Graphical explanation of the backward (unfolding) problem [1].

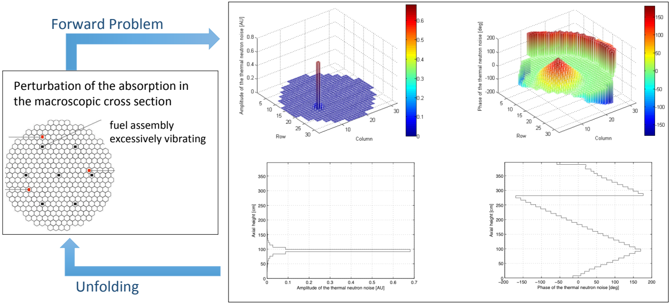


Figure: Graphical explanation of the backward (unfolding) problem [1].

Analysed Signals

Frequency Domain Related

Simulation conducted using CORESIM tool [2] using a Pressurized Water Reactor (PWR) with:

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

CORESIM output

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

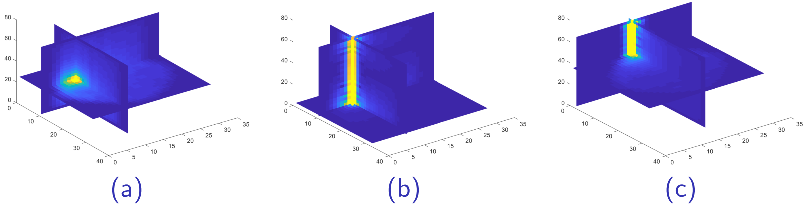
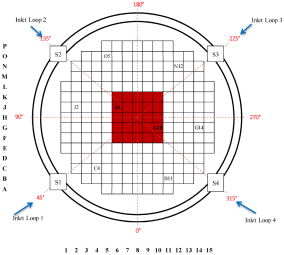


Figure: Response to **a:** *Localised*, **b-c:** *Propagating-Travelling* perturbations.

Signals were corrupted to emulate fewer available sensor measurements (5% and 20% of measurements respectively). Fast and Thermal responses were concatenated into a $64 \times 64 \times 26$ volume, zero-padded to $64 \times 64 \times 32$ for convenience.

Time Domain Related

Simulation were conducted using Simulate-3K (S3K) [3] on a model of the four-loop Westinghouse PWR mixed core. Below, a radial view of the nuclear reactor core model utilised. The red central zone represents a 5×5 cluster of fuel assemblies (FAs).



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

Table: Synchronised vibration of a 5 $\times$ 5 fuel assemblies central cluster.

Scenario	Perturbation	Frequency	Amplitude	ID
1	5 $\times$ 5 cluster FAs	WN	1 *mm*	1 0 0 0
	5 $\times$ 5 cluster FAs	WN	0.5 *mm*	1 0 0 0
2	5 $\times$ 5 cluster FAs	1 Hz	1 *mm*	0 1 0 0
	5 $\times$ 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

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

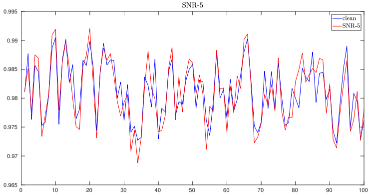
Scenario	Combined Perturbations	ID
5	Temperature (5) & flow (6)	0 0 1 1
6	5×5 FA (2) & temperature (5)	1 0 1 0
7	5×5 FA (1) & temperature (5)	1 0 1 0
8	5×5 FA (4) & temperature (5)	0 1 1 0
9	5×5 FA (3) & temperature (5)	0 1 1 0
10	5×5 FA (2) & flow (6)	1 0 0 1
11	5×5 FA (1) & flow (6)	1 0 0 1
12	5×5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

SIMULATE-3K output

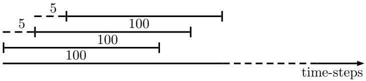
Each detector recorded a response to the perturbation:

- recording duration: 100s,
- sampling rate $= 100Hz$
- with perturbation amplitude $= 0.5mm$ and $1mm$

We get $\mathbf{x} \in \mathbb{R}^{10001}$ signals. Window sampling augment these vectors to produce $\mathbf{x} \in \mathbb{R}^{1980\times 100}$. Furthermore, signals were corrupted by the addition of White Gaussian Noise at signal-to-noise ratios (SNR) 10 and 5.



(a)



(b)

Figure: **a:** Signal obtained by means of S3K with noise added at $SNR = 5$. **b:** Signal sampling.

Our 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

3D-CNN and LSTM

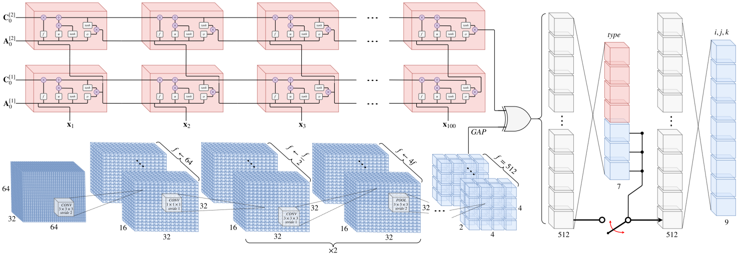


Figure: Unified framework for time and frequency domain perturbation type classification and coordinate regression. An LSTM network at the top for time domain signals, and a 3D CNN below for frequency domain signals.

Multi-Objective Learning – 3D-CNN

Formally, the multi-task optimisation objective is minimised with respect to **W** parameters given $\mathcal{D}$ input data as:

$$\mathscr{L} = \sum_{i}^{T} \lambda_i \ell_i(\mathcal{D}; \mathbf{W}), \text{where } \ell_i \text{ represents:} \tag{1}$$

- $\ell_1(y_1, \widehat{y}_1)$, negative log-likelihood loss for perturbation type classification
- $\ell_2(y_2, \widehat{y}_2)$, $L2$ loss for perturbation coordinate regression

Concretely, the 3D CNN is trained by minimising

$\mathscr{L}(\mathcal{D}; \mathbf{W}, \lambda_1, \lambda_2) =$

$$\begin{aligned} -\frac{1}{N}\sum_{i=1}^{N}\Bigg[\frac{\lambda_1}{P}\sum_{j=1}^{P}\left[y_1^j \log(\widehat{y}_1^j) + (1 - y_1^j)\log(1 - \widehat{y}_1^j)\right] + \\ -\frac{\lambda_2}{C}\sum_{c=1}^{C}\|y_2^c - \widehat{y}_2^c\|^2\Bigg]_i \end{aligned} \tag{2}$$

Multi-Label Classification – LSTM

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:

$$\mathscr{L}(y, \widehat{y}) = -\frac{1}{PN} \sum_{j=1}^{P} \sum_{i=1}^{N} \Big[y_j \log(\widehat{y}_j) + (1 - y_j) \log(1 - \widehat{y}_j) \Big]_i \tag{3}$$

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.

Multi-Objective Learning – 3D-CNN

Table: 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	(i, j, k) Regression 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**

Multi-Label Classification – LSTM

Table: 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
10	28/14/14	100	1	81.16
5	28/14/14	100	1	77.43

Discussion and Conclusions

We proposed:

- A Deep-CNN approach to unfold the induced neutron noise in the frequency domain
- A Deep-CNN approach to identify core perturbation types
- An LSTM network to recognise of perturbation in the time domain
- We are moving toward a unified framework capable of simultaneously accommodating signals in the time and frequency domain.

Future Work

In the future, we plan to extend our studies to other types of data, simulated in the Time and Frequency domains utilising the same/multiple reactor cores, to test the sensitivity of our framework to different reactor characteristics.
Furthermore we intend to investigate real data coming from nuclear power plants, in pursuit of a framework suitable for simultaneously handling Time and Frequency domain signals for the localisation and classification of nuclear reactor anomalies.

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- Paul Scherrer Institute (Switzerland): Dionysios Chionis and Abdelhamid Dokhane
- University of Lincoln (United Kingdom): Georgios Leontidis, Stefanos Kollias

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Thank you