CORTEX
Core monitoring techniques and experimental validation and demonstration

WP3 – Development of advanced signal processing & machine learning methodologies for analysis of plant data

CORTEX Final Workshop, 21-22/6/2021

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WP3 objectives:

- Analysis of Plant Data and Neutron Current & Flux Modelling through Advanced Signal Processing (ASP)
- Analysis of Plant Data and Neutron Current & Flux Modelling via Machine Learning (ML) Techniques

WP3 objectives (1):

Analysis of Plant Data and Neutron Current & Flux Modelling through Advanced Signal Processing (ASP)

Advanced Signal processing methods included

- Fast Fourier transform, Hilbert transformations, multiresolution wavelet analysis
- Non-parametric inversion methods: artificial neural networks & fuzzy logic

This part built on former work that had been performed by the project partners such as UPM, UJV, CEA and partly from ICCS-NTUA.

WP3 objectives (II):

Analysis of Plant Data and Neutron Current & Flux Modelling via Machine Learning (ML) Techniques

Machine learning focused on current research on deep learning (DL) and deep neural networks (DNNs) produced by UoL and ICCS-NTUA.

- Required large (simulated) dataset generation by experts in the field – either in the frequency, or the time domain (Chalmers, PSI)
- Included development and use of state-of-the-art DNNs, trained through supervised, but also unsupervised learning algorithms
- Prepared the path for application of these algorithms to real plant data in WP4, taking into account the lack of labelling information.

WP3 Specific Targets:

- Detection of abnormal fluctuations & classification based on their safety impact (Localization & Type Classification Tasks)
- Calculation of the induced noise
- Inversion of the reactor transfer function using estimation results from WP1
- Handling of scarcity of in-core instrumentation
- Learning in selected reactor(s) and transferring it to others (Simulated vs Real)
- Application and adaptation of the developed techniques to real data in WP4.

WP3 Tasks:

- Task 3.1: Generation of basic scenarios and simulated data
- Task 3.2: Advanced data processing in time and frequency
- Task 3.3: Data analysis using machine learning and DNNs

Task 3.1: Generation of basic scenarios and simulated data

- Subtask 3.1.1: Definition of basic scenarios

  → Types of perturbations in Time, or Frequency Domains

- Subtask 3.1.2: Early generation of simulated data

  → Generation of adequate numbers of simulated data (with some scenarios)

- Subtask 3.1.3: Further generation of simulated data

  → Generation of complete set of scenarios and related simulated datasets.

Task 3.2: Advanced data processing in time and frequency

- Subtask 3.2.1: Multiresolution wavelet-based processing of signals

  → examine the benefits of wavelet based feature extraction for ML analysis

- Subtask 3.2.2: Noise analysis in processing of plant data

  → detect and extract noise characteristics that can be used in further analysis

- Subtask 3.2.3: Reconstructing missing data

  → improve performance by averaging aggregated data for missing value reconstruction

- Subtask 3.2.4: Preliminary processing of real data

  → extract and analyse characteristics of real plant data.

Task 3.3: Data analysis using machine learning and DNNs

- Subtask 3.3.1: Extraction of model parameter values from data

  → Train different ML/DL architectures

- Subtask 3.3.2: Training intelligent systems for efficient data analysis

  → Extend state-of-the-art to fit 3-D localization & classification problems

- Subtask 3.3.3: Using pre-trained networks through transfer learning

  → Adopt transfer learning and domain adaptation methodologies

- Subtask 3.3.4: Preliminary analysis of plant data and adaptation

  → Develop DNNs trained with simulated data; use them to analyse real data.

WP3 in a nutshells:

- Summary of Goals
- Summary of Achievements

WP3 Summary of Goals

- Develop techniques that allow detecting anomalies in nuclear reactor core:
  - abnormal vibrations of fuel and core internals,
  - flow blockage,
  - coolant inlet perturbations.
- Use non-intrusive monitoring of neutron noise (fluctuations in neutron flux recorded by in-core and ex-core instrumentation).
- WP3 developments were completed in early 2020; efforts were then focused on applying the techniques to real plant data, within WP4.

WP3 Summary of Achievements

- Development of a variety of signal processing and analysis methods:
  - working in the frequency and time domains,
  - finding coherence and phase correlation relationships in noisy signals,
  - using signal transformations (Hilbert-Huang; Discrete Wavelet)
- Development of a rich machine and deep learning framework for:
  - unfolding of reactor transfer functions,
  - enabling the classification and localization of perturbations,
  - examining single, multiple and simultaneous reactor perturbations.

Examples of Significant Outcomes

- Examples of Signal Processing & Analysis
- Examples of Machine Learning Analysis

Examples of Signal Processing & Analysis

- Monitor signal characteristics and infer correlations and anomalies
- Optimise wavelet transformation of signals

Examples of Signal Processing results (1):

i)The profiles of the APSDs are similar to each other. However, there are completely defective sensors that can be clearly differentiated (J06-2, N08-2)
ii)The main differences refer to the area enclosed under APSDs, (noise variance) & the amplitude of the resonance peaks.

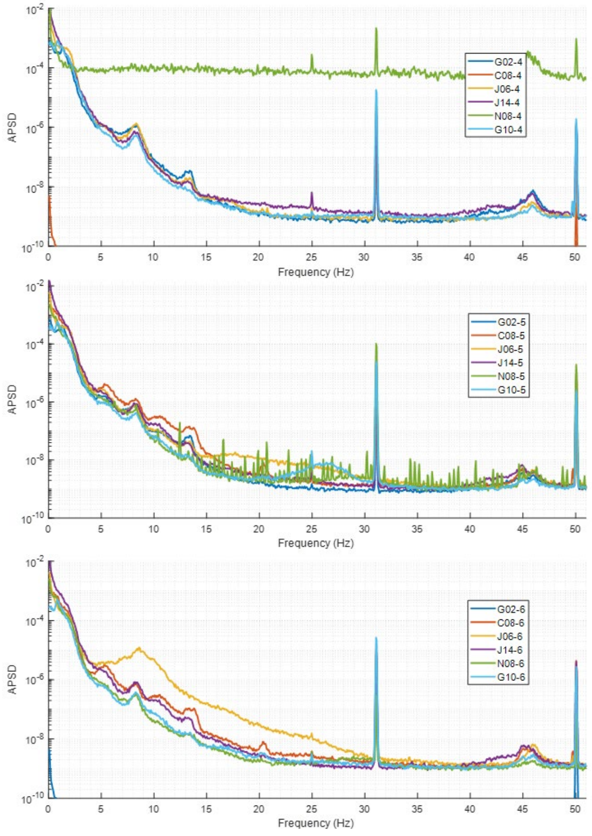
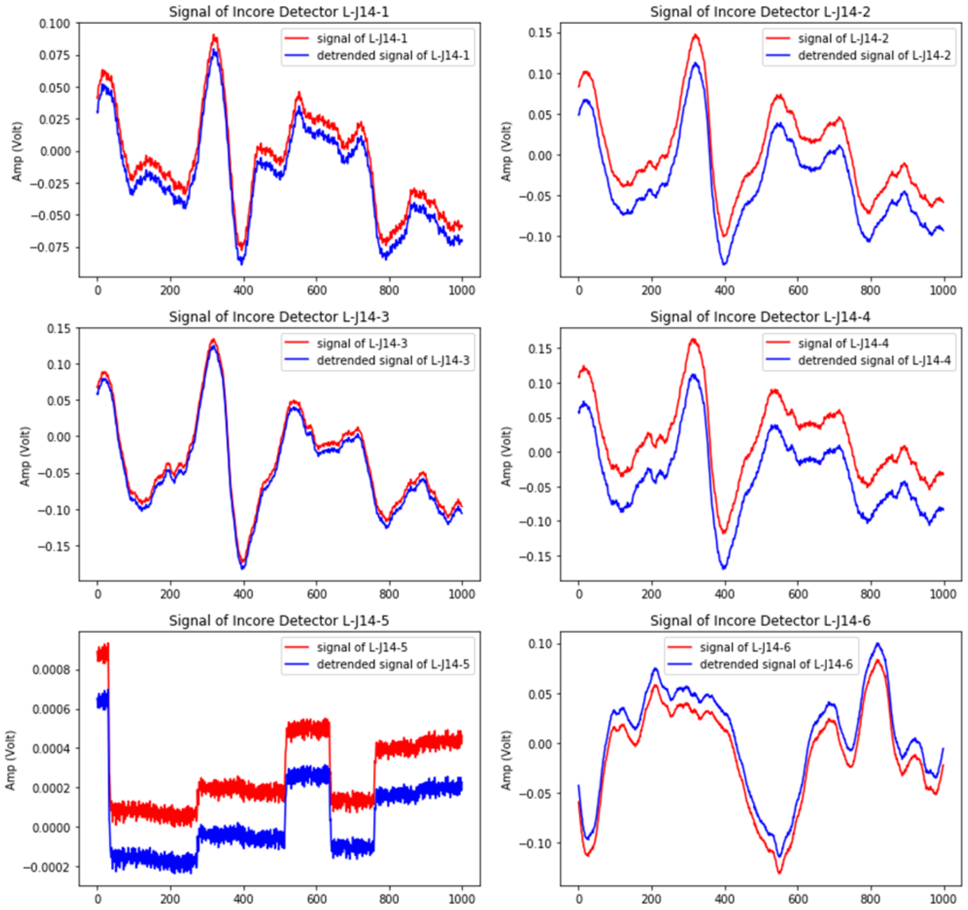


Figure 1: APSDs of the sensors in the same level 4, 5, and 6, from up to down, respectively

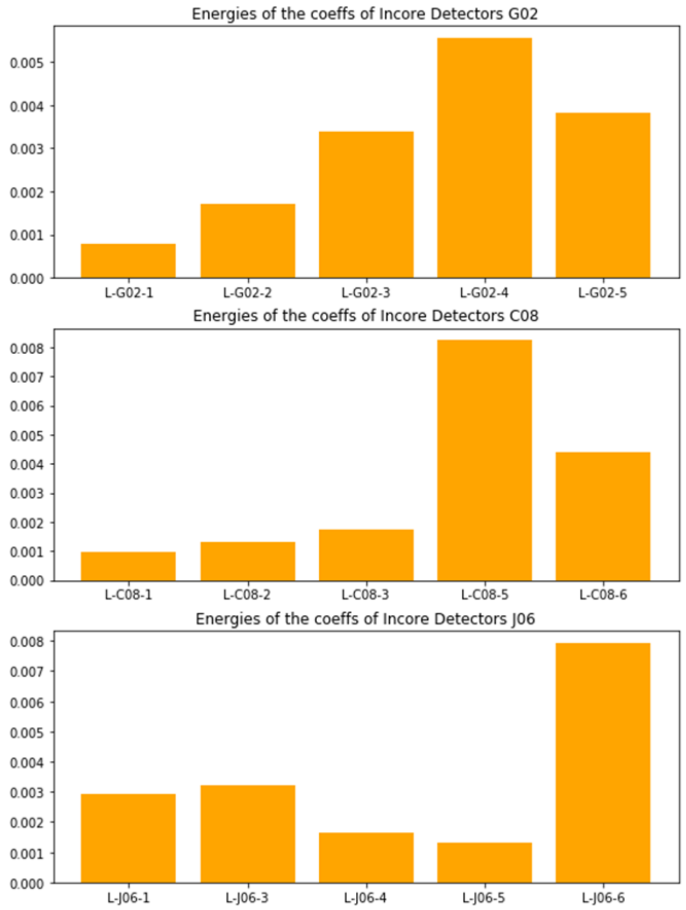
Examples of Signal Processing results (II):

(i) signals at vertical positions at top of core (1, 2) & at bottom (6) exhibit similar values of trend;
(ii) values at bottom of core (5) are two orders of magnitude smaller than nearby vertical detectors
→ this detector may be malfunctioning;
ii) detectors near middle of core have different trend levels; small at position 3 & larger at position 4.



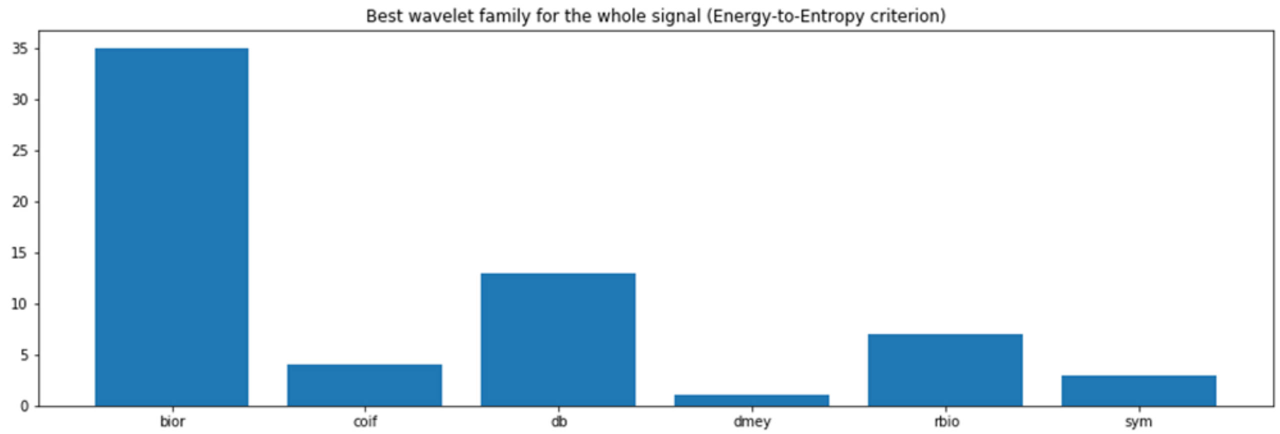
Examples of Wavelet Analysis results (1):

(i) wavelet coefficients' energy levels are higher at bottom positions (5, 6) than top (1, 2) for most in-core detectors,
(ii) at 5th axial level (bottom) all detectors witness large wavelet coefficients' energy, except of J06,
(iii) detectors J06/C08 have complementary behavior wrt wavelet coefficients' energy at core bottom.



Examples of Wavelet Analysis results (II):

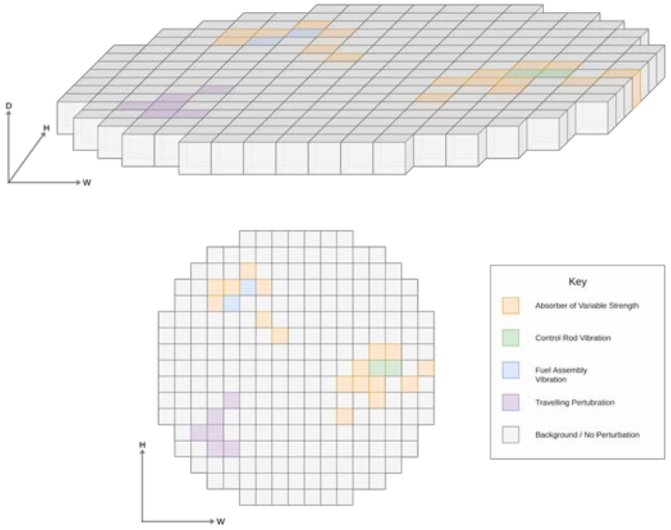
(i) The biorthogonal mother wavelet family accurately described the majority of the signals



Examples of Machine Learning Analysis

- Target semantic segmentation, i.e., classification of each voxel in the input data to a semantic (class) perturbation label.
- Develop 3-D fully-convolutional encoder-decoder segmentation networks, generating a prediction mask of perturbation class per voxel.
- Simultaneously detect & localize multiple reactor core perturbations for, e.g., a 32x32x34 voxel space, given only 48 In-core & 8 Ex-core detectors.
- Non-trivial task, successfully tackled in WP3 and evaluated on a large variety of simulated input data cases.

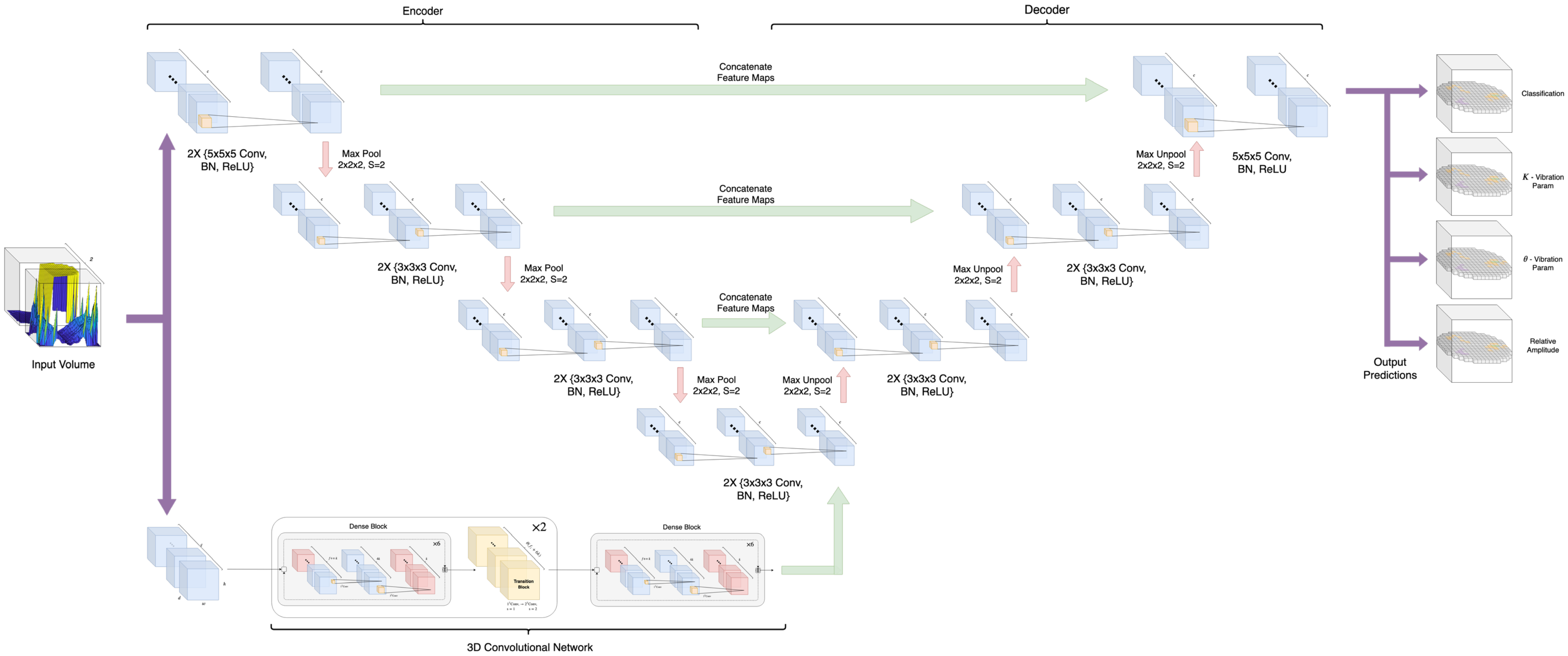
Semantic Segmentation: predictions (coloured voxels) represent sources at which a perturbation type originated from.



AVS = Absorber of Variable Strength,
FA = Fuel Assembly Vibration,
CR = Control Rod Vibration,
TP = Travelling Perturbation,
BV = Core Barrel Vibration,
BG = Background / No Class

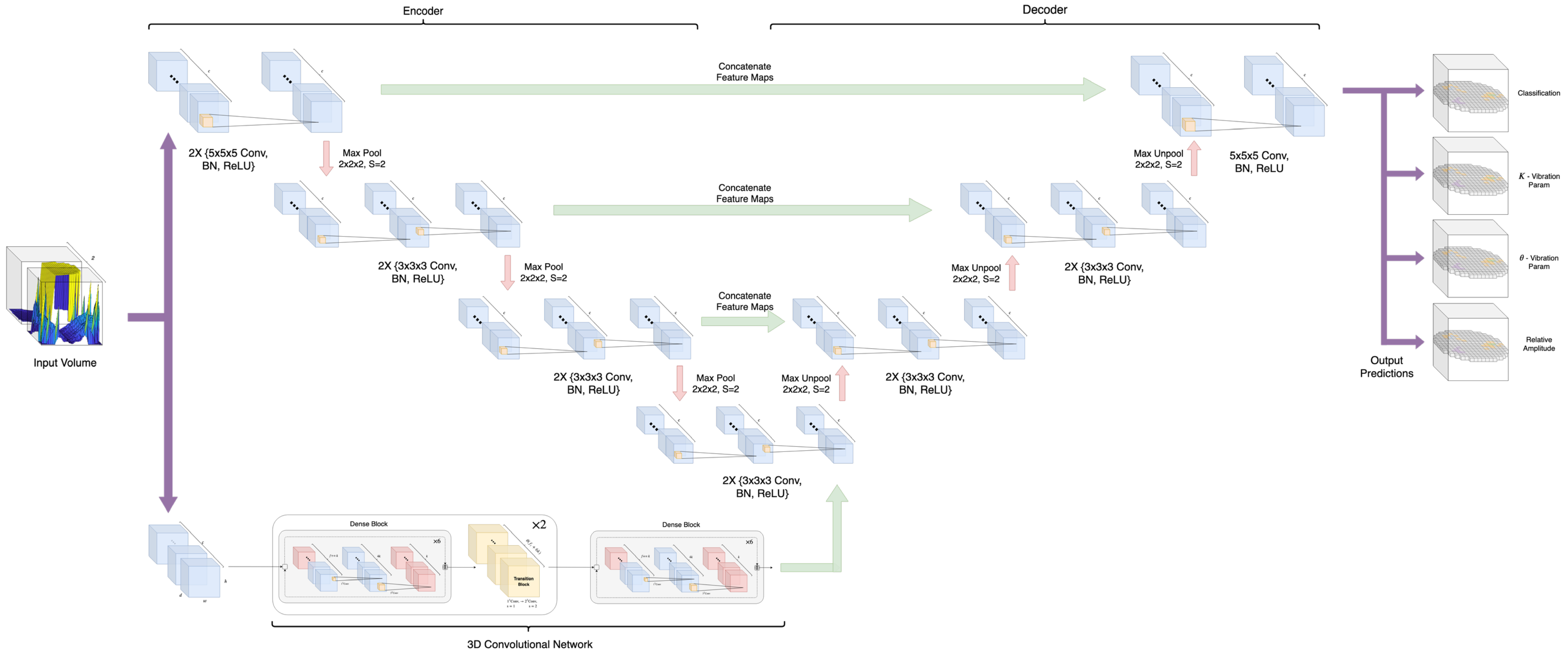
Per Class Voxel Accuracies *					
Simultaneous Combinations	**Accuracy Error (%)**				
	AVS	FA	CR	TP	BV
1 - 600	15.68	00.81	02.82	00.20	00.11
1 - 1400	16.57	00.11	03.02	00.42	00.23

Novel DNNs & Domain Adaptation: from simulated to real data (I)



A combined network of voxel-wise semantic segmentation and a 3-D Convolutional Neural Network, producing four volumetric predictions: perturbation classification, k-theta vibration parameters and relative perturbation amplitude.

Novel DNNs & Domain Adaptation: from simulated to real data (II)



From simulated to real data

- Transfer Learning (The real plant data and the simulated data are of near identical distributions)
- Domain Adaptation (The real data is unlabelled; the distribution of simulated and real data is different)
- Self-learning (Unlabelled plant data alone is used; learning deep feature representations is performed through auxiliary tasks).

Details of the Technical Achievements

- This presentation does not aim to present the details of the technical achievements related to ASP and ML/DL methods, particularly related to the application to real plant data.
- In the following, and particularly in the presentations related to WP4, such details will be presented.
- In the rest of this presentation, we will focus on what has been achieved and which are the current prospects, by the end of the CORTEX project.

Moving from 09/2017 to 08/2021 (I)

- When preparing and starting CORTEX in 2016 & 2017, our technical partners had started developing and implementing Deep Learning methodologies and Deep Neural Networks.
- That is why the main novelty of CORTEX has been in:
  - the refinement and application of state-of-the-art DNNs (2-D, 3-D CNN, RNN models, U-Net, autoencoder, Conv-LSTM)
  - developing supervised, unsupervised, self-supervised learning contexts
  - transfer learning, domain adaptation; considering uncertainty
  - application to time/frequency simulated real & real plant data.

Indicative (ML) Publications

- A. Durrant, G. Leontidis, S.Kollias, L. Torres, C. Montalvo, A. Mylonakis, C. Demaziere, P. Vinai, "Detection and Localization of Multiple In-Core Perturbations with Neutron Noise-based Self-Supervised Domain Adaptation", ANS M&C 2021, 3-7 October 2021.

- G. Ioannou, T. Tasakos, A. Mylonakis, G. Alexandridis, C. Demaziere, P. Vinai, A. Stafylopatis, "Feature Extraction and Identification techniques for the Alignment of Perturbation Simulations with Power Plant Measurements", ANS M&C 2021, 3-7 October 2021.

- C. Demazière, A. Mylonakis, P. Vinai, A. Durrant, F. Ribeiro, J. Wingate, G. Leontidis, S. Kollias, "Neutron Noise-based Anomaly Classification & Localization Using ML", PHYSOR 2020, Cambridge, UK, 29/3-2/4/2020.

Indicative (ML) Publications

- A. Durrant, G. Leontidis, S.Kollias, "3D CNN - RNNs for reactor perturbation unfolding and anomaly detection, EPJ Nuclear Sci. Technol. 5, 20, 2019; also in FISA, Pitesti, Romania, 4-7/6/2019 (best paper award).

- F. Ribeiro, F. Caliva, D. Chionis, A. Dokhane, A. Mylonakis, C. Demaziere, G. Leontidis and S. Kollias, "Towards a Deep Unified Framework for Nuclear Reactor Perturbation Analysis", IEEE Symposium Series on Computational intelligence, Bangalore, India, 18-21 November 2018.

- F. Caliva, F. S. Ribeiro, A. Mylonakis, C. Demaziere, P. Vinai, G. Leontidis, and S. Kollias, "A deep learning approach to anomaly detection in nuclear reactors," IEEE International Joint Conference on Neural Networks, Rio de Janeiro, Brazil, 8-13 July 2018.

Moving from 09/2017 to 08/2021 (II)

- A great research work has been achieved in CORTEX in developing and adapting state-of-the-art DL – DNN models for unfolding stationary perturbations on simulated data; interesting results have already been obtained with real plant data as well.
- Extending the models and results adapting emerging ML/DL models (self-supervising, gaussian frameworks, graphs, continual learning) on the obtained and new plant data is an on-going R&D activity, building on and beyond CORTEX.
- The implementation of the research has been achieved by data transfer from field expert partners to technology partners and exchange of the results; sharing & use of the created ML tools by expert partners was not possible.

Moving from 09/2017 to 08/2021 (III)

- In the meantime ML and DL approaches have been considered as being part of the Artificial Intelligence Landscape of methods.
- The European Commission has elaborated a lot on AI and ML/DL guidelines and prospects during the above period.

AI: What Happened in Europe in the last 3 years?

2018:
- Declaration of Co-operation in AI
- A European Approach to AI (EC, April 2018)
- A Coordinated Plan on AI (EC, December 2018)

2019:
- Ethics Guidelines for Trustworthy AI (HLEG EC, April 2019)
- Building Trust in AI (HLEG EC, April 2019)
- Policy & Investment Recommendations for Trustworthy AI (HLEG AI, June 2019)

AI: What Happened in Europe in the last 3 years?

2020:
- Data Governance Act (EC, November 2020)
- Berlin Declaration of Digital Society and Value-based Digital Governance (EC, December 2020)

2021:
- Revised Coordinated Plan on AI (EC, April 2021)
- Rules for AI (EC, April 2021)

AI Vision

“Accelerating Digital Innovation by leveraging Inclusive AI”

- Putting AI at the Service of People, Society & Environment
- Fostering Creativity, Economic Growth & Digital Transformation
- Creating a technology-enabled future that is more democratic, equitable and sustainable for all and for the common good

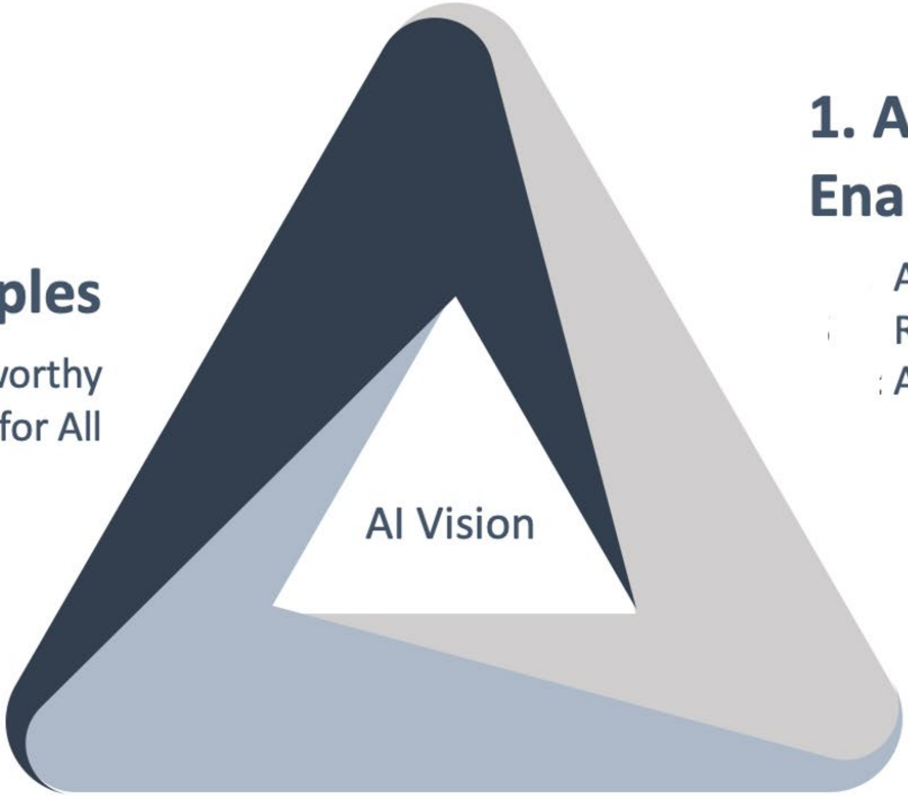
Key Policy Areas

1. AI Infrastructural Enablers

AI Infrastructures,
Research, Education & Skills Capital,
AI Innovation ecosystem

3. AI Principles

Ethical. Trustworthy
& Democratic AI for All



2. AI Application Areas

AI-driven Economic
Transformation and Growth
AI for the Public Sector

EC: AI Coordinated PLan 2021

“Build Strategic Leadership in High Impact Sectors”

- AI for climate and environment *
- Next Generation AI for Health
- Strategy for Robotics with AI
- AI in the public sector
- AI in law enforcement, migration, asylum
- AI for smarter, safer, sustainable mobility
- AI for sustainable agriculture

The Next Step for AI-enabled analysis of plant data

Moving from the developed black-box ML/DL methods to AI

- Trustworthy
- Explainable
- Unbiased
- Democratized
- User-Centered
- Infrastructure Agnostic

Thank you