High-Rate Dynamic Data Augmentation and Damage Classification

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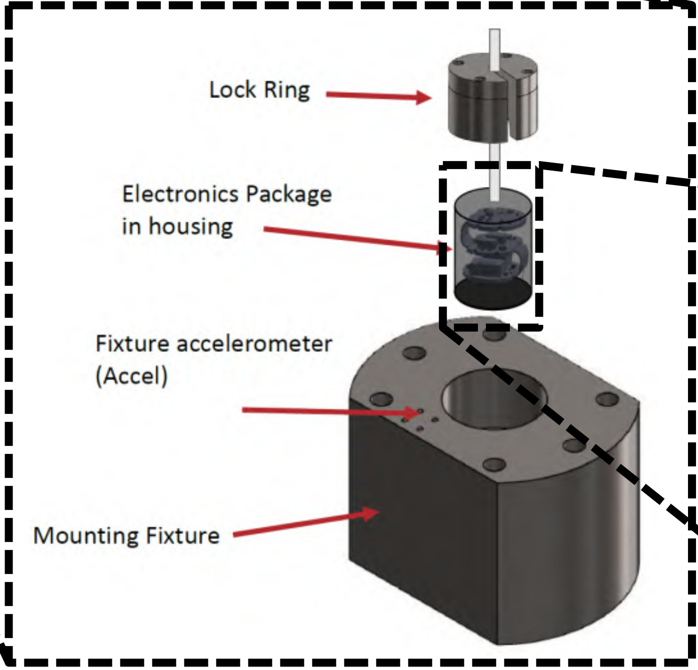
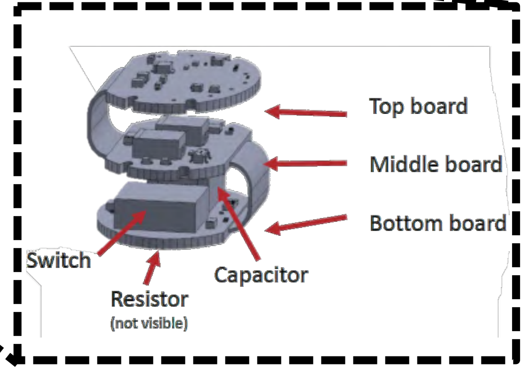
Experimental Setup of High-Rate Dynamic Test

Low-Acceleration Experiment

Drop Tower



Mounting Fixture

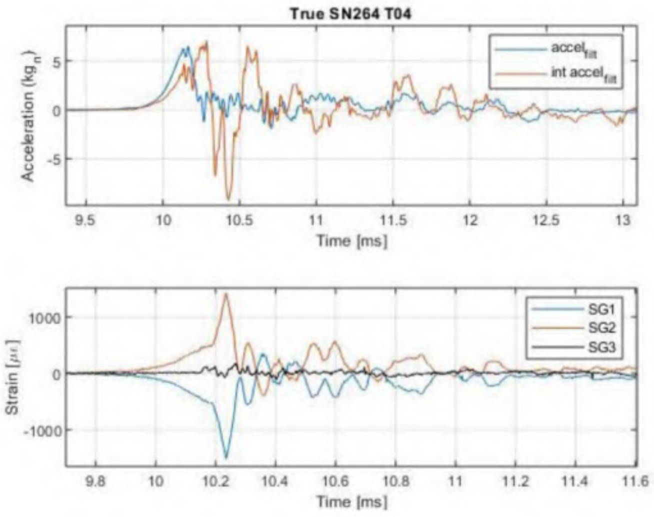


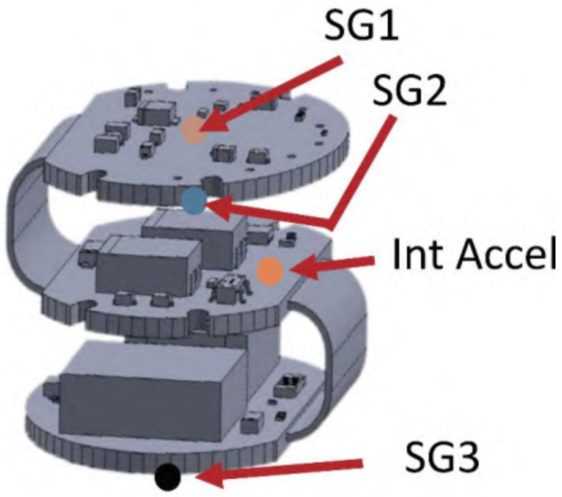
Test Article

Data courtesy of Dr. Jacob Dodson at AFRL/Eglin

Data Acquisition

- Dataset collected at 1MHz and 5.5ms
- 5 sensors used for each tests
- Reliability of the capacitor is lost after 6th experiment
  - Dataset is divided into Healthy and 5 levels of damage





Overview of the Proposed Methodology

CVAE

- Dimension reduction and feature extraction of the data set
- Trained using the original dataset as input

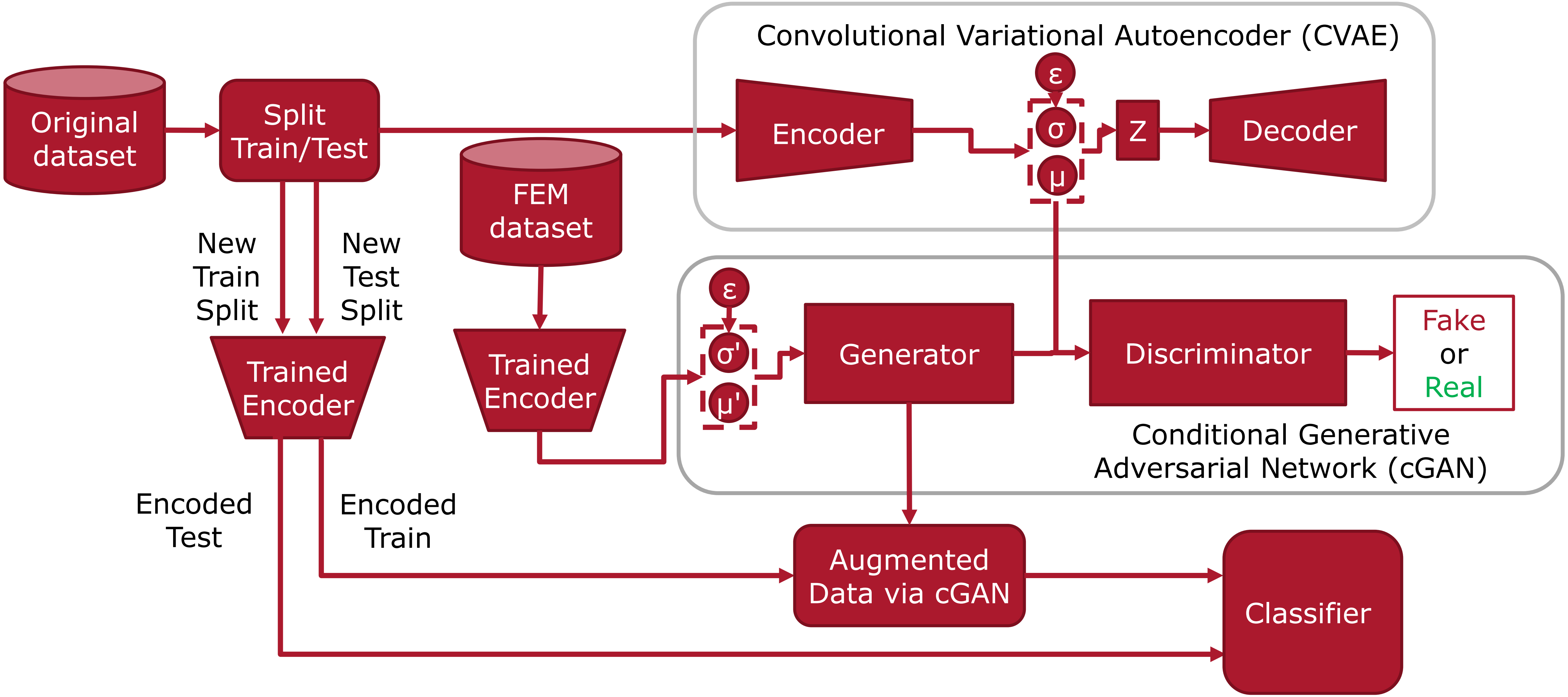
FEM-Enhanced cGAN

- Augment original encoded dataset to improve classification accuracy
- Uses FEM encoded data as seed of the model
- Discriminator compares generated dataset with original set

Classification

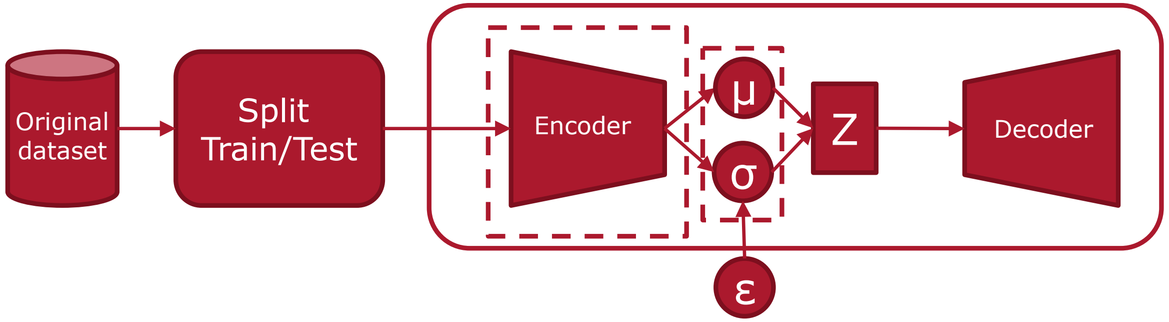
- Uses encoded dataset
- Training data is a mix of FEM dataset and original dataset
- Testing data is only original dataset

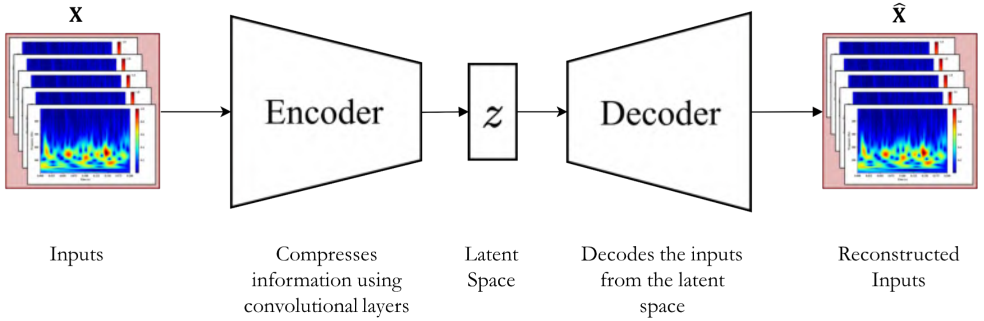
Data Augmentation via FEM-Enhanced cGAN



Convolutional Variational Autoencoder (CVAE)

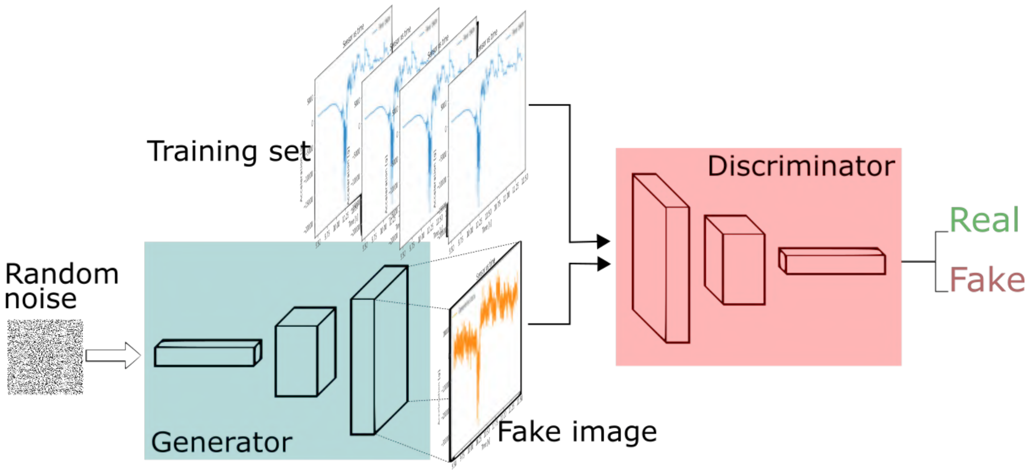
- Deep learning technique for nonlinear dimension reduction
- Encoder uses a neural network to obtain the compressed data $\mathcal{Z}$ in a latent space
- Decoder uses dataset $\mathcal{Z}$ to recreate the original dataset
- Loss function based on signal reconstruction and normal distribution of the data
  - $l_R = \frac{1}{2}\sum_{j=1}^{M}\left[1 + \log(\sigma_j)^2 - \mu_j^2 - \sigma_j^2\right]$
  - $l_L = \sum_{j=1}^{M}(x_j - \hat{x}_j)^2$





Conditional Generative Adversarial Network

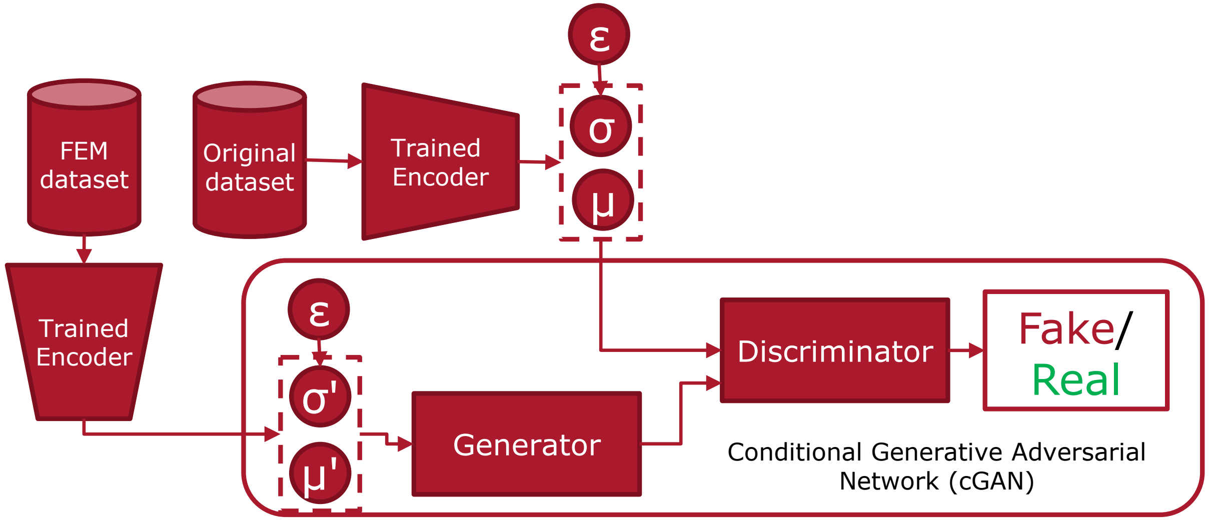
- cGAN: a neural network designed for synthetic data generation
- Two components
  - Generator: generates the synthetic data
  - Discriminator: Try to predict if the data given is real or fake
- Uses random noise as input

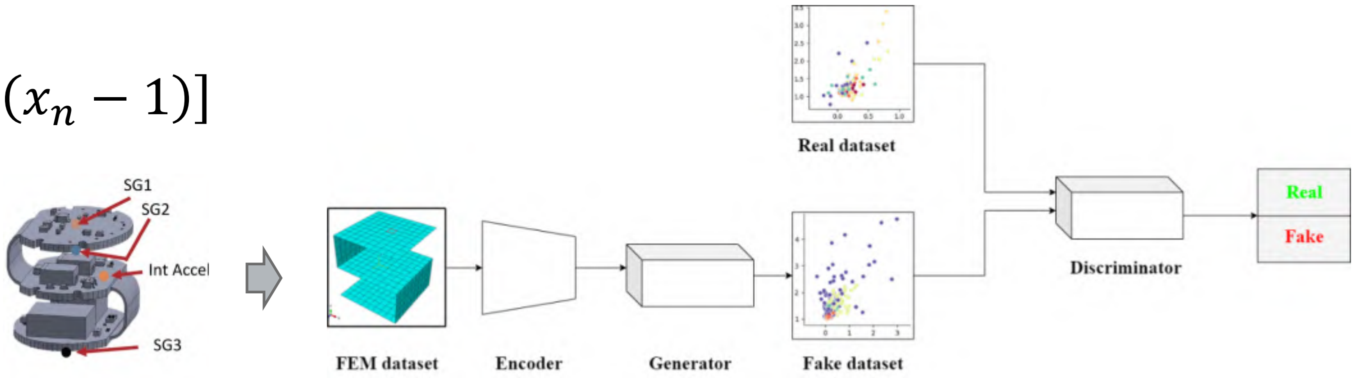


https://thispersondoesnotexist.com/

FEM-Enhanced cGAN

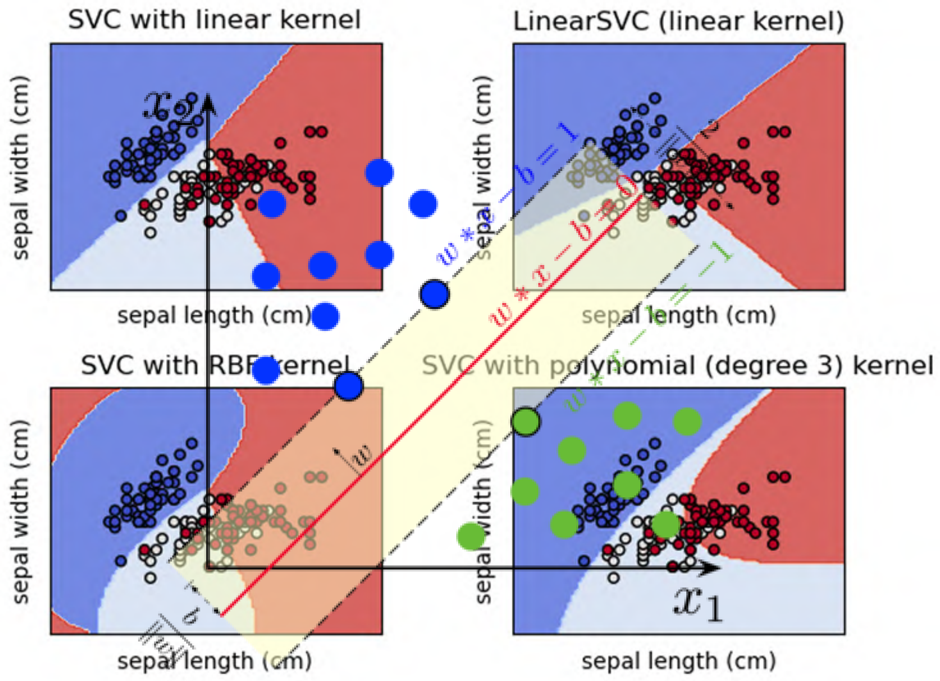
- FEM response as seed instead of driving with random noise
  - Expected a faster converging in the training set
- Encoded dataset is used since it has smaller dimension
- Loss function defined as:
  - $L = -w_n[y_n \cdot \log x_n + (1 - y_n) \cdot \log(x_n - 1)]$





Classification – Support Vector Machine (SVM)

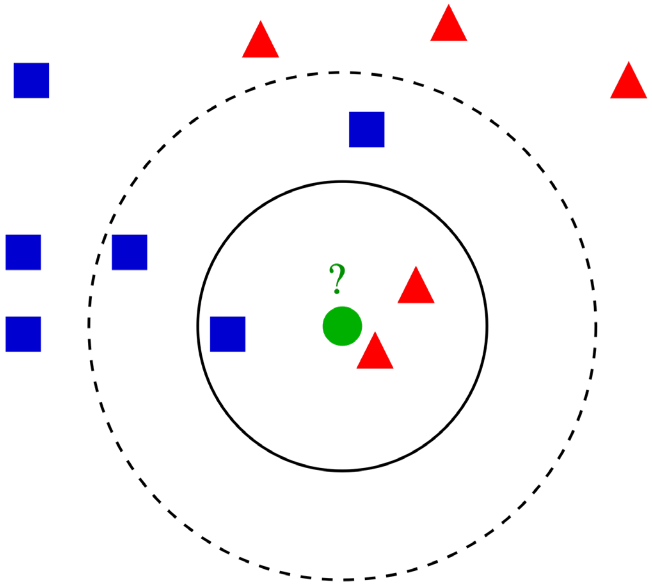
- Linear classifier
  - Supervised learning technique
  - Good performance for high dimensional data
- Kernel function for classification
  - $K(X_1, X_2) = \langle X_1, X_2 \rangle$
  - $K(X_1, X_2) = e^{-\gamma \|X_1 - X_2\|^2}$
- Minimizes the error for the function
  - $t(w, \xi) = \frac{1}{2}\|w\|^2 + \frac{C}{m}\sum_{i=1}^{m} \xi_i$



Source: https://scikit-learn.org/stable/modules/svm.html

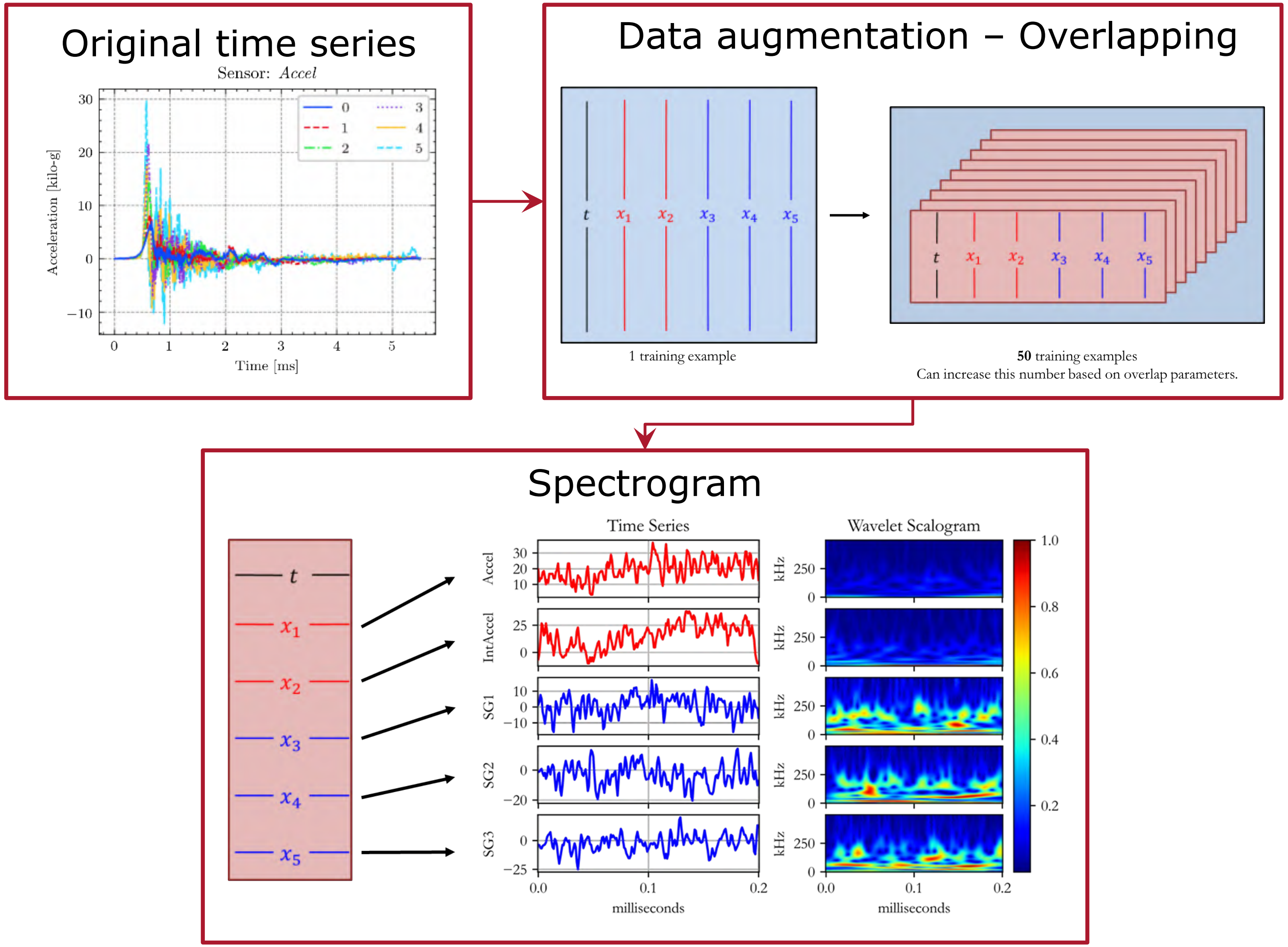
Classification – K-Nearest Neighbors (KNN)

- Machine learning classifier
  - Supervised learning technique
  - Good performance for small datasets
- Classification based on distance of points
  - Order the points from the nearest
  - $\|X_1 - x\| \leq \cdots \leq \|X_n - x\|$
  - Classify the new point based on the K nearest classes



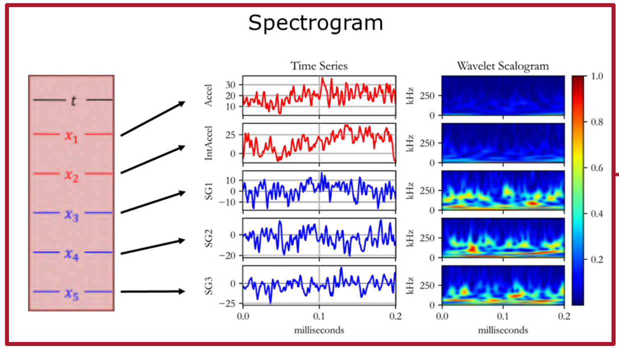
Signal Pre-Processing

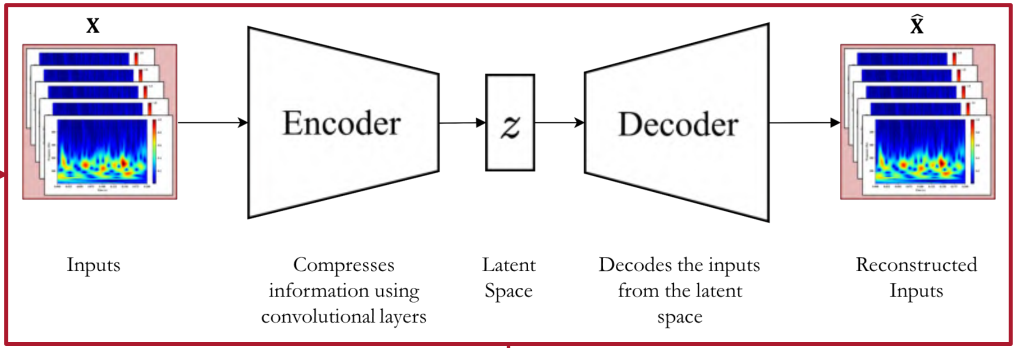
- Moving window with overlaps
  - Extract original vector into a big dataset
- Frequency and temporal information
  - Spectrograms
  - Wavelet transform
  - Data is transferred to a 2D representation

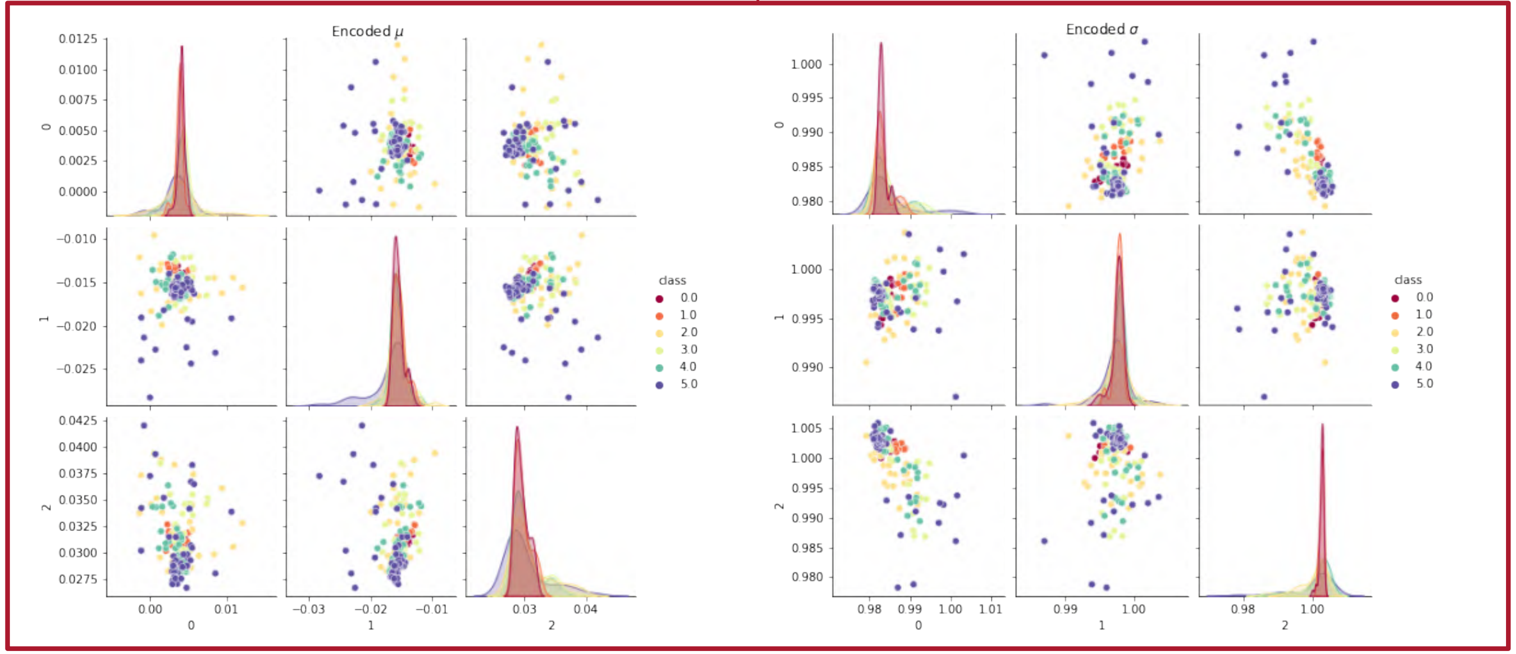


Dimension Reduction via CVAE

- Spectrogram is input into encoder
  - 3 latent dimensions
  - Small number of features for classification
  - Dimensionality

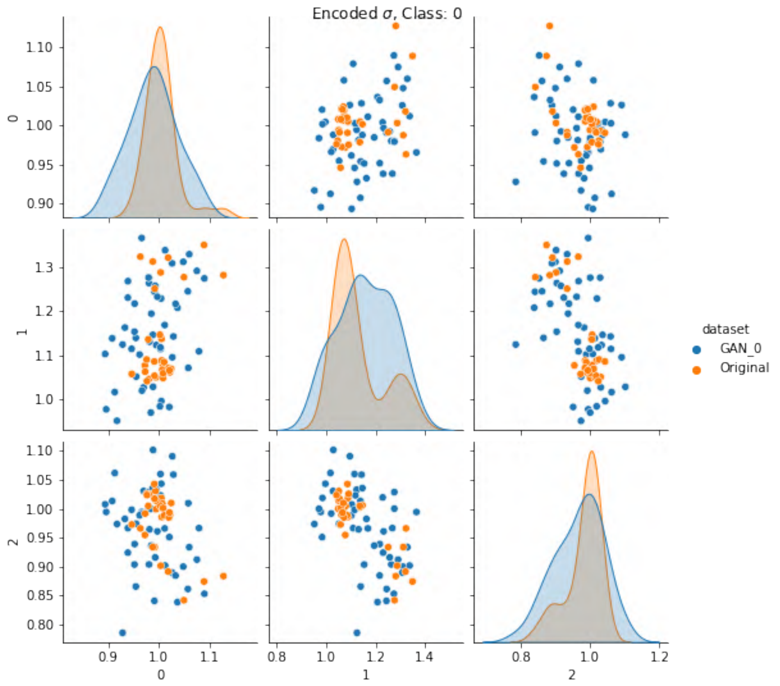


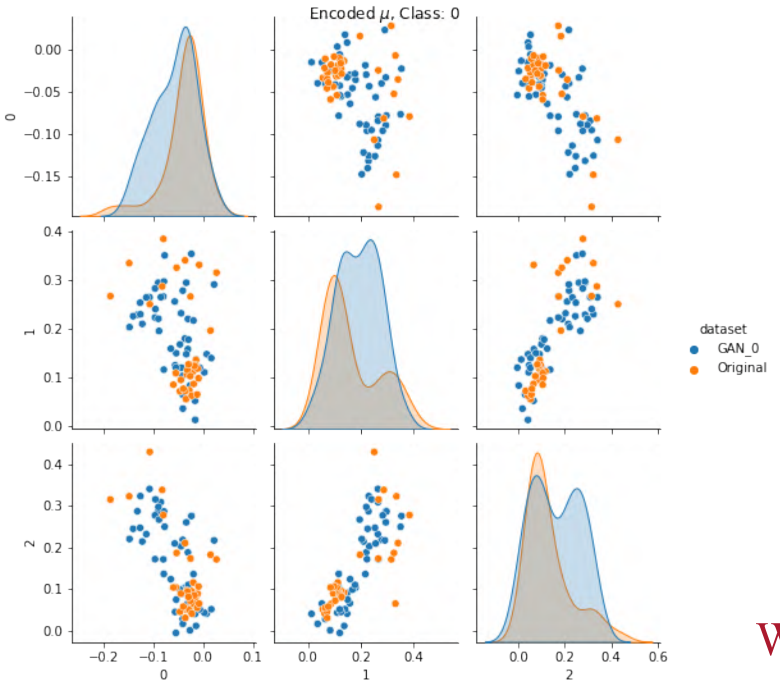




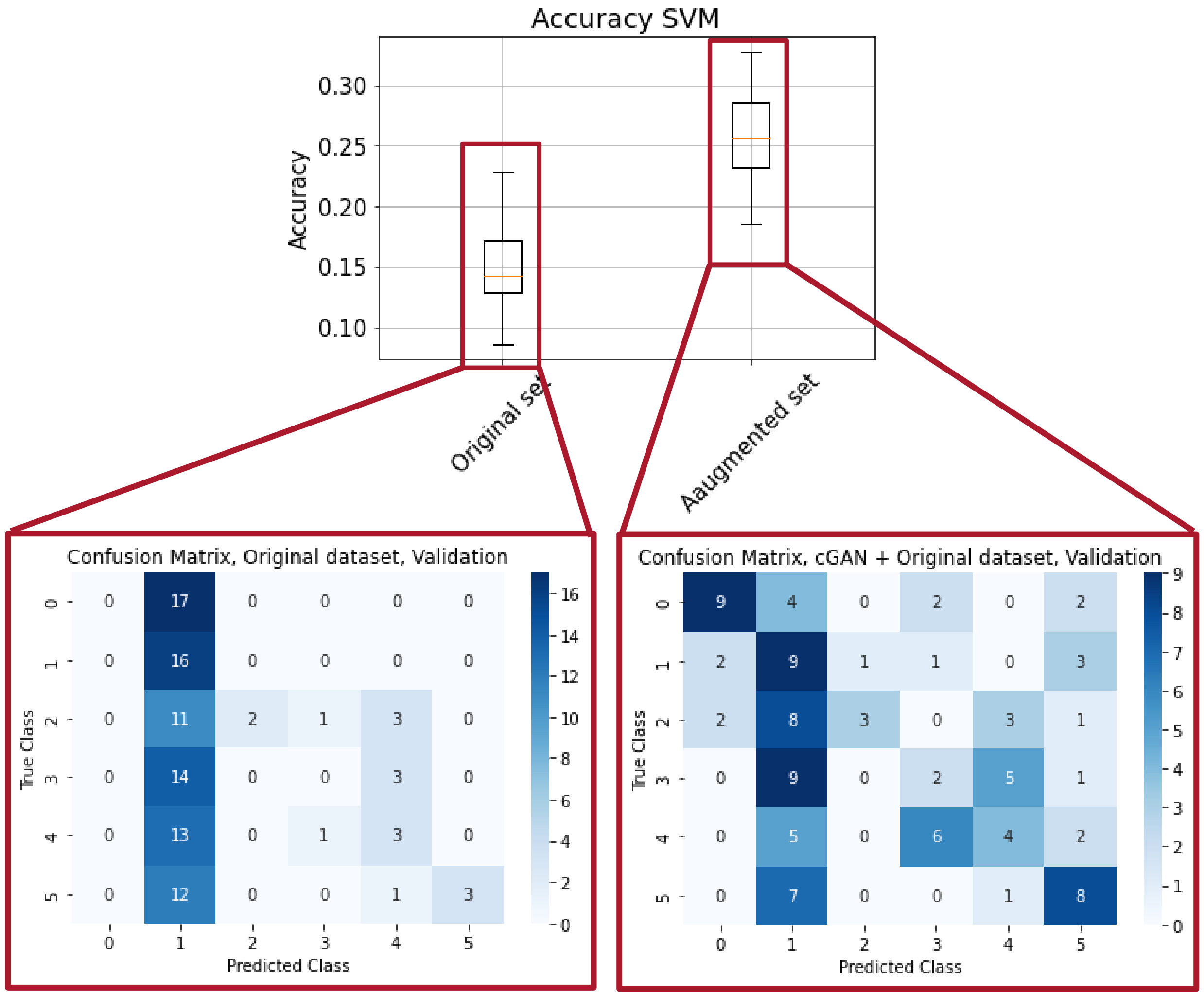
FEM-Enhanced cGAN Results

- Modification of loss function to avoid mode collapsing
  - $L = -w_n[y_n \cdot \log x_n + (1 - y_n) \cdot \log(x_n - 1)] + \frac{\sigma_n^2}{\sigma_n^2 + (x_n - \mu_n)^2}$
- Augmented dataset has similar distribution to the original dataset
  - It occurs in all dimensions and with all classes



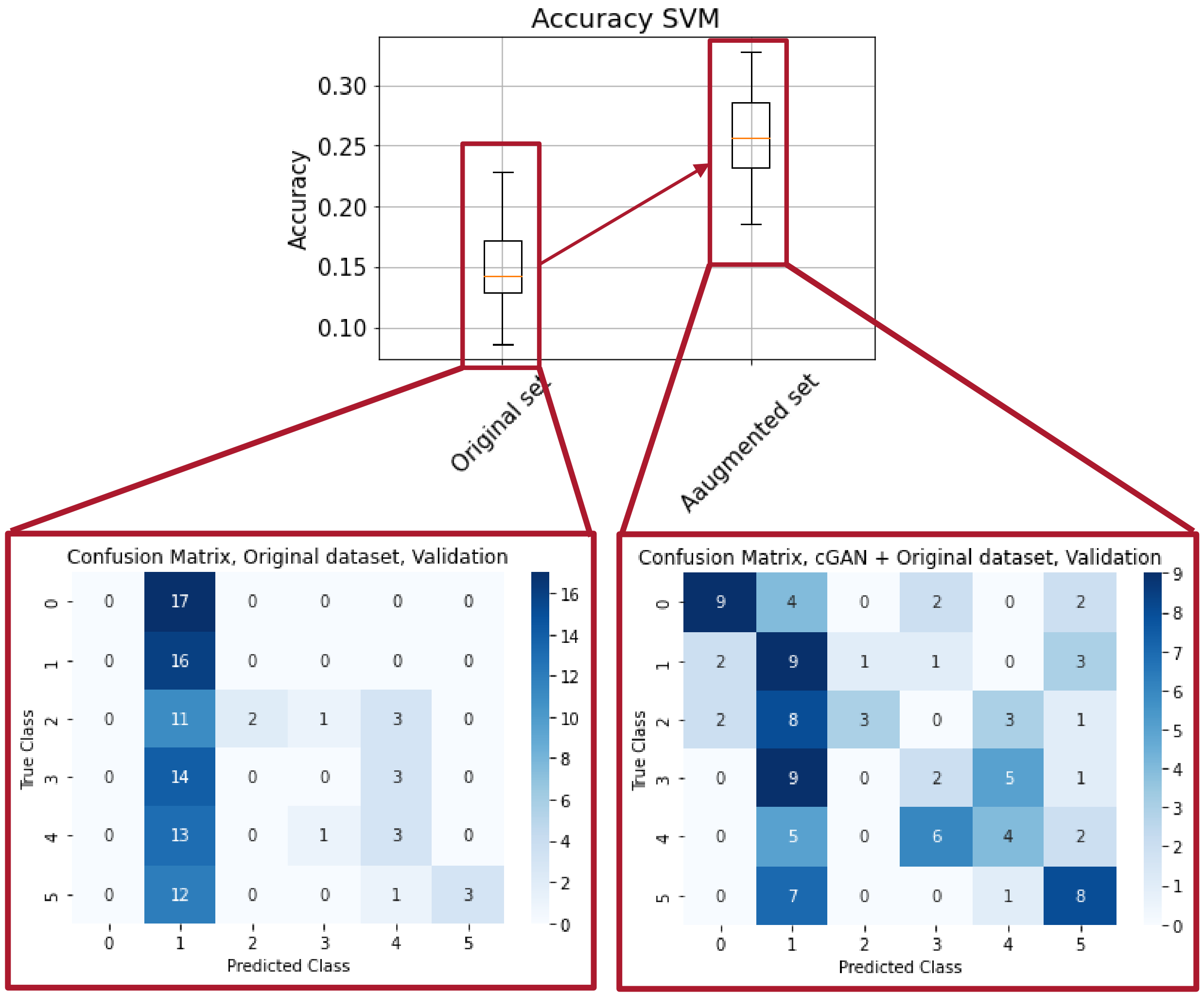


Damage Classification – Initial Results

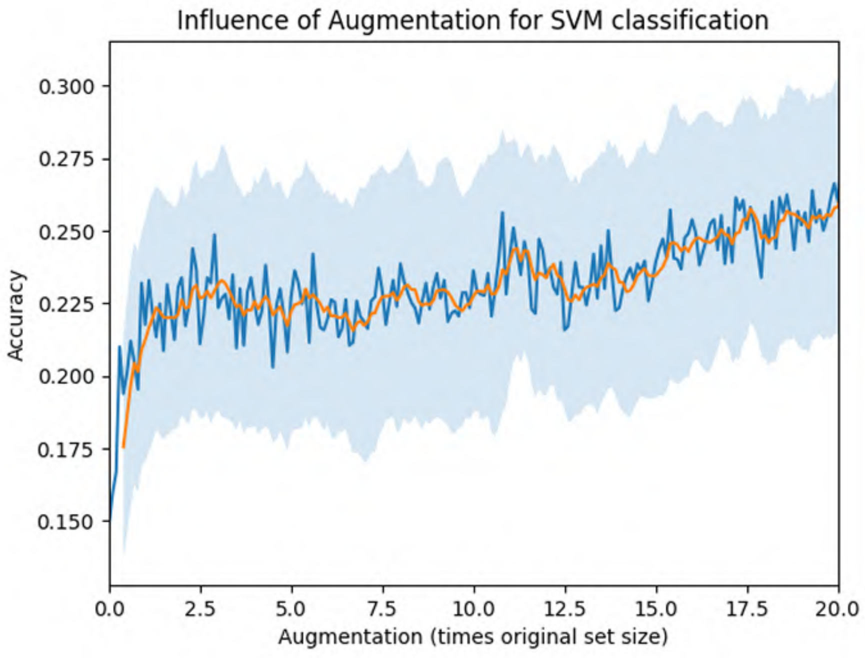


- Accuracy used as metric for evaluation
  - $Accuracy = \frac{TP+TN}{TN+TN+FP+FN}$
- Statistical run with different shuffling was applied
- Original dataset classification tends to predict all points in one set

Damage Classification – Initial Results

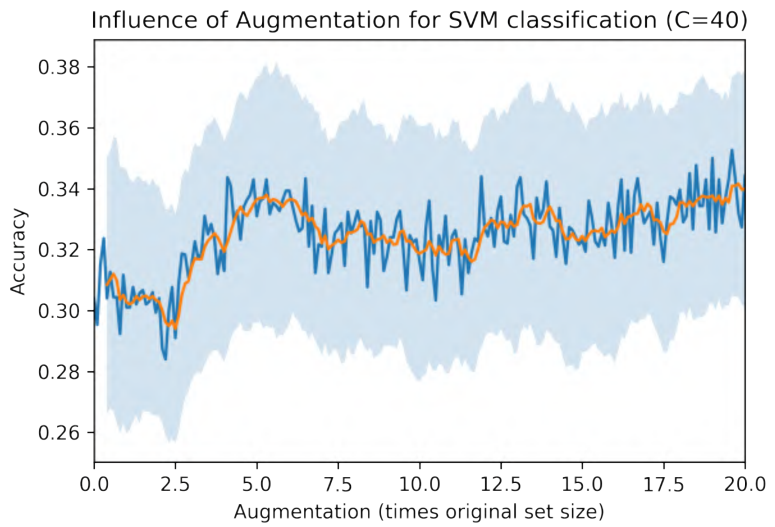


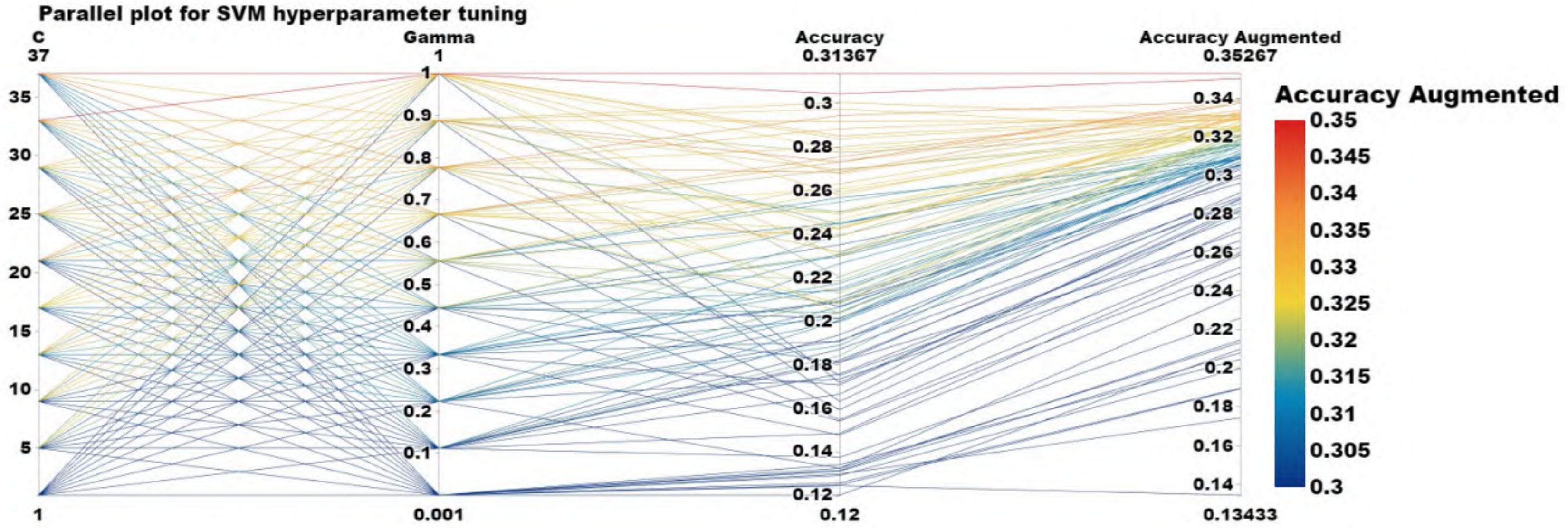
- How the augmentation influence the accuracy?

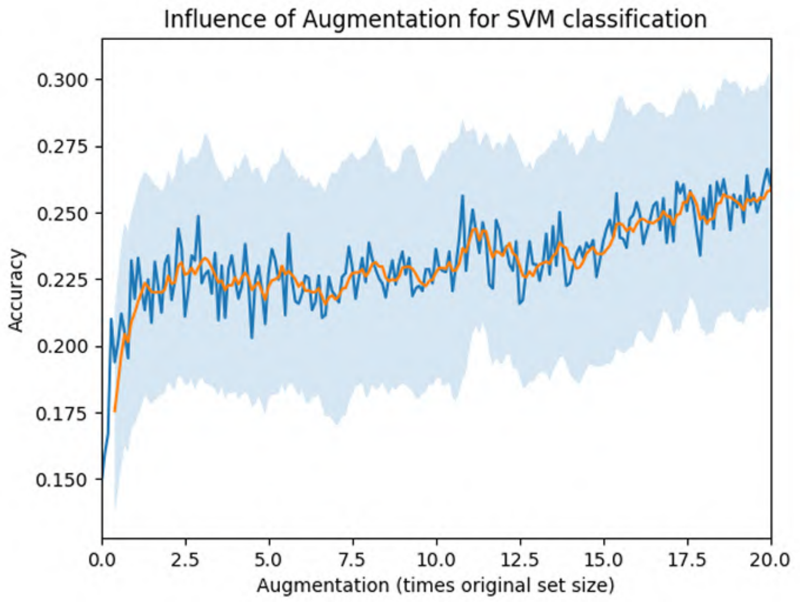


Hyperparameter Tunning for SVM

- High regularization parameter C and kernel coefficient γ had a better performance
  - $K(X_1, X_2) = e^{-\gamma \|X_1 - X_2\|^2}$
  - $t(w, \xi) = \frac{1}{2}\|w\|^2 + \frac{C}{m}\sum_{i=1}^{m} \xi_i$

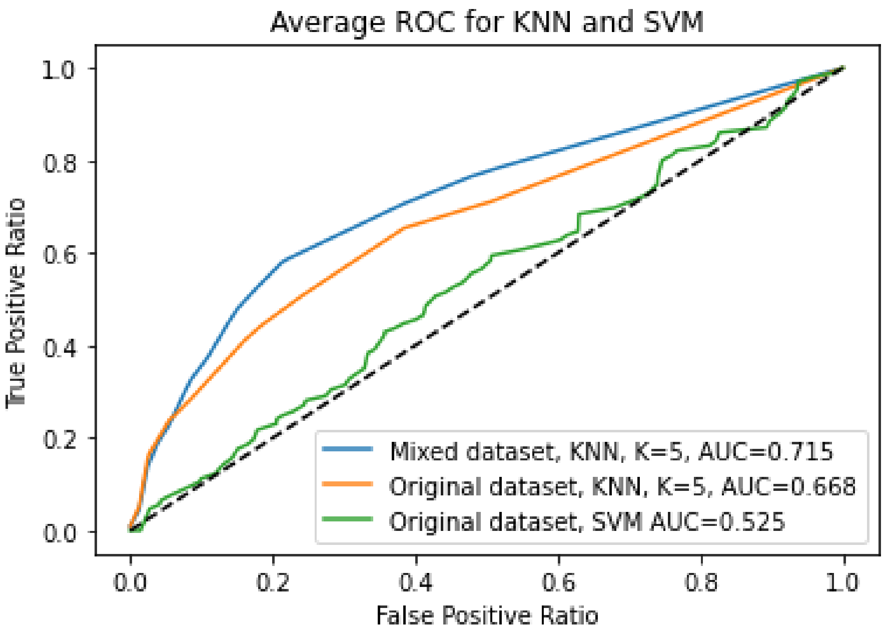


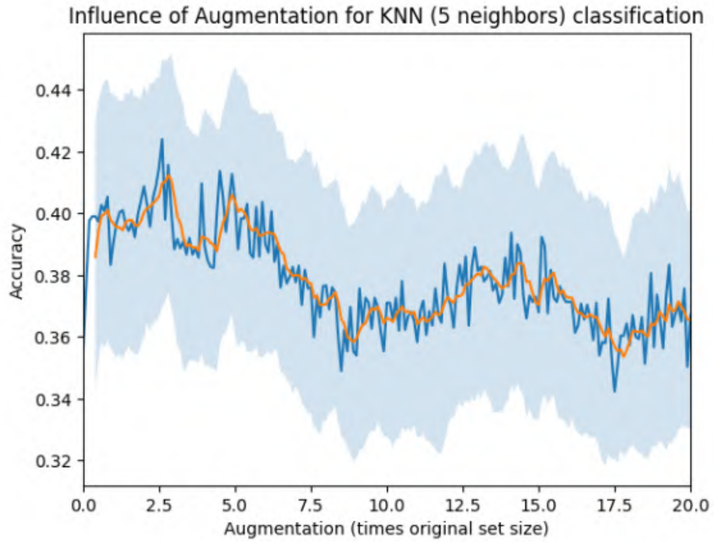


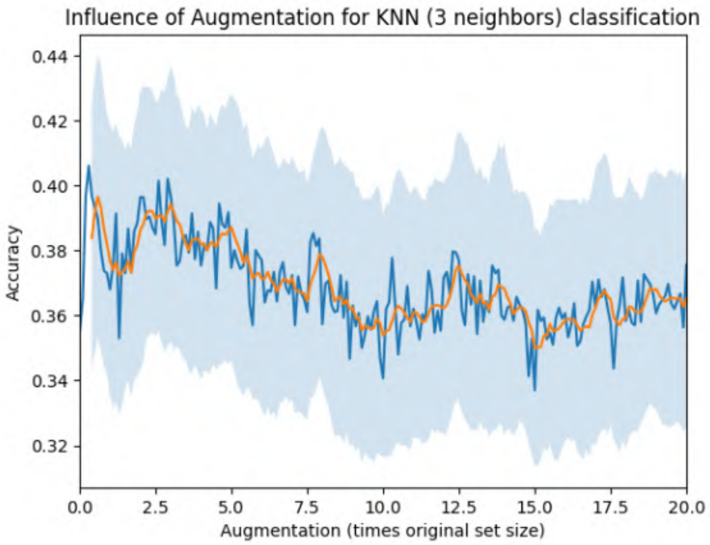


Damage Classification – KNN

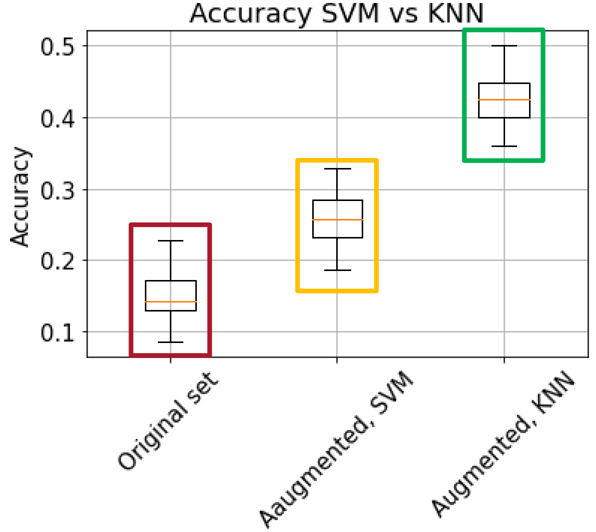
- Among different classifiers KNN had the best accuracy after augmenting the dataset
- Hyperparameter tunning showed best results using 3 and 5 neighbors
- Higher accuracy with small augmentation

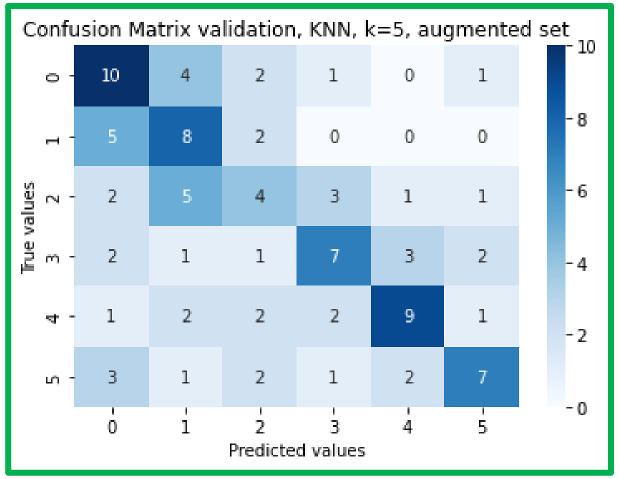


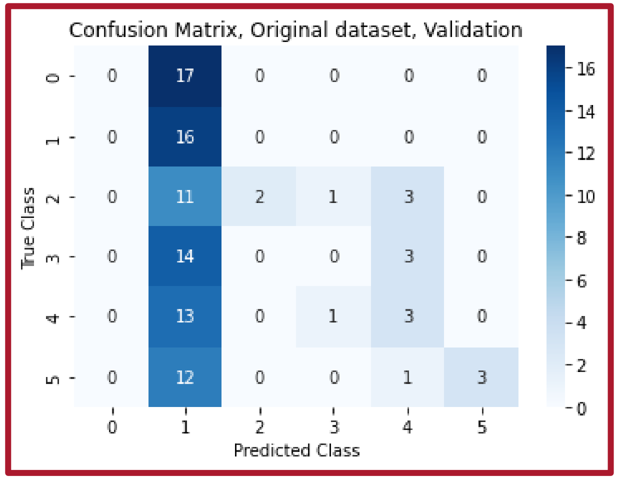


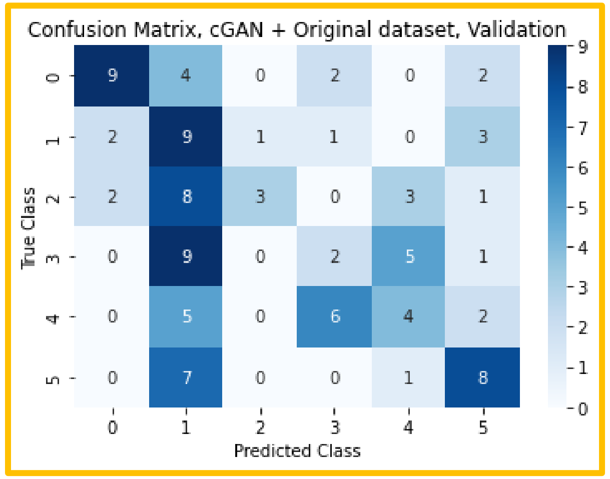


Comparison of Different Approaches









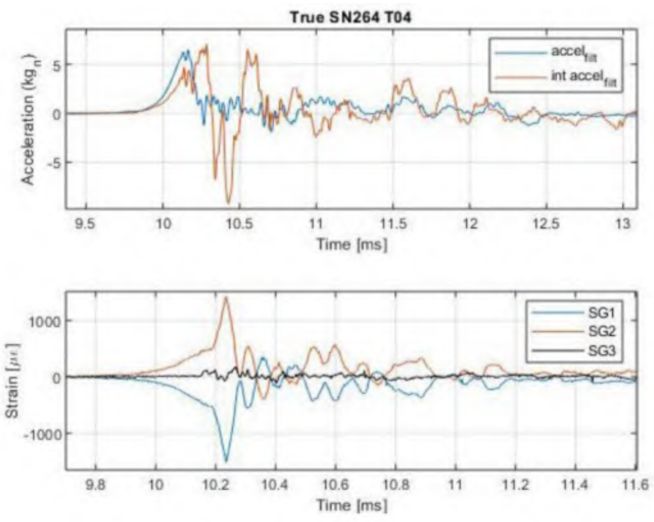
- Increase of around 30% in the accuracy compared to doing nothing
- KNN has a better performance when increasing only 2.5 times the original set
- SVM has higher accuracy as more data is added
- Some techniques does not have significant changes with augmentation

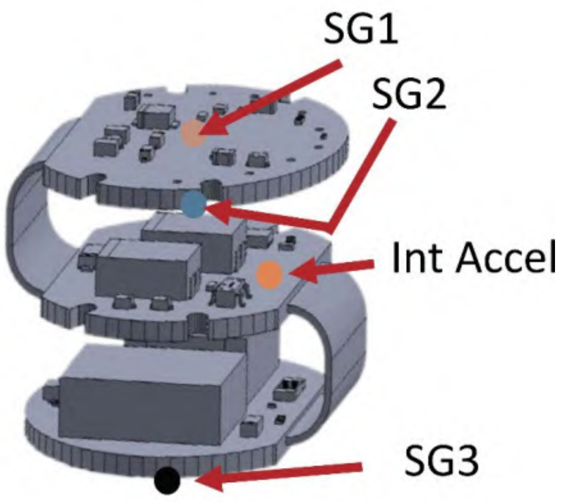
Summary

- Convolutional variational autoencoder applied for feature extraction and dimension reduction
- Conditional generative adversarial networks poses a good solution for limited sets
  - Enhancing cGAN using the FEM dataset as seed poses an easier hyperparameter tunning, better synthetic dataset and faster converging
- Data-augmented will have significant influence on different machine learning algorithms
- But…

Recap of the Available Data

- Dataset collected at 1MHz and 5.5ms
- 5 sensors used for each tests
- Would be better to validate the approaches via more controllable experimentations



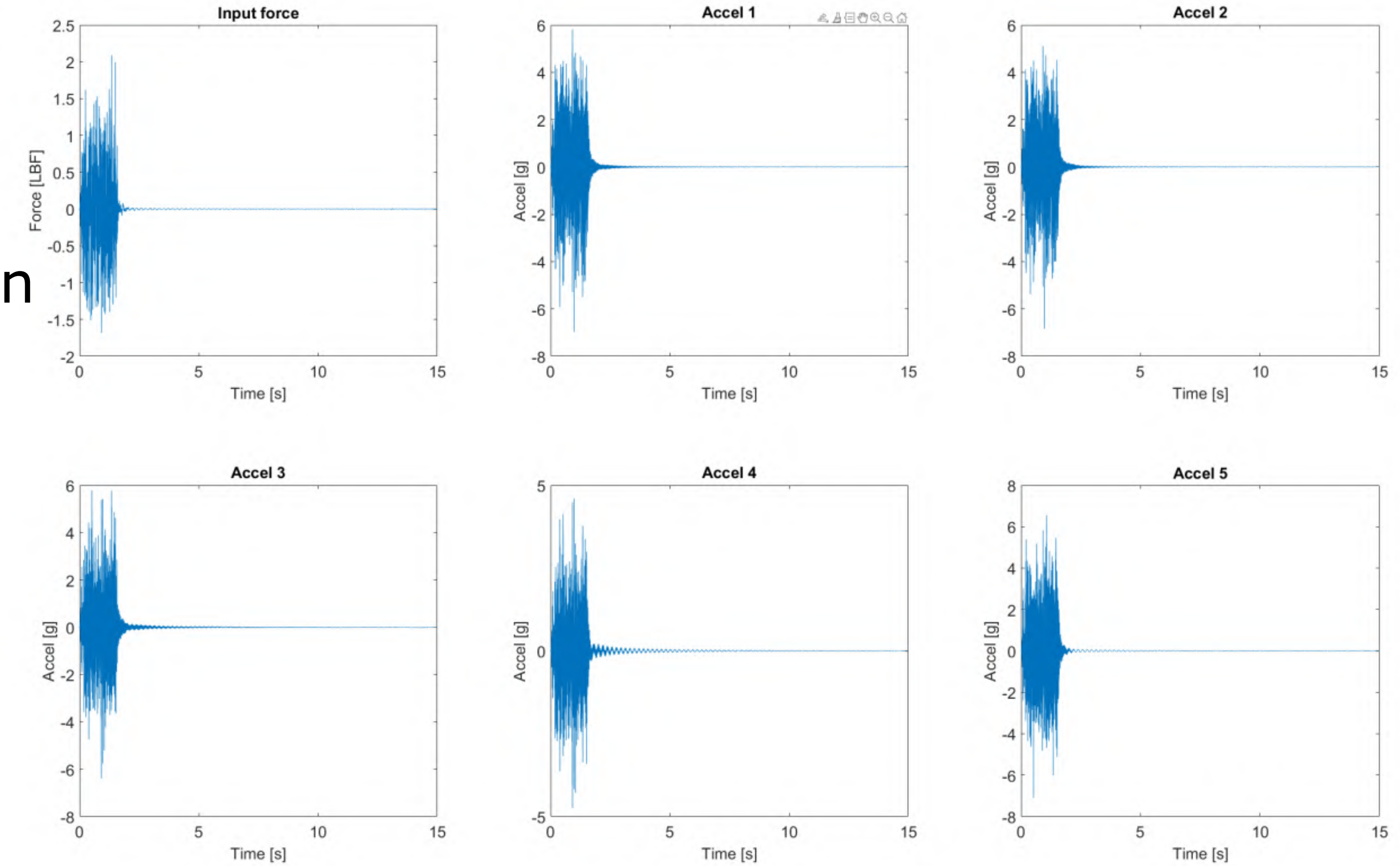


Data from a Simple Structure

- Place 5 accelerometers and record vibrational response
- Extract 6 mode shapes (up to 225Hz)
- FE model available and can provide data in the same locations for physics-enhanced learning
- Nonlinearities will be introduced to mimic different stages of “damages”

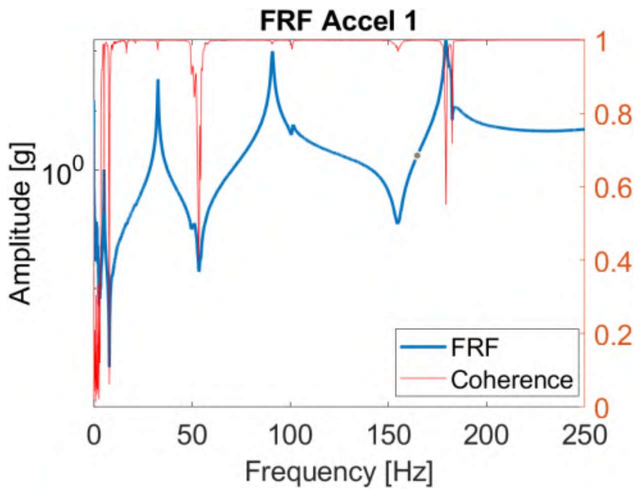
Response of the Plate Structure

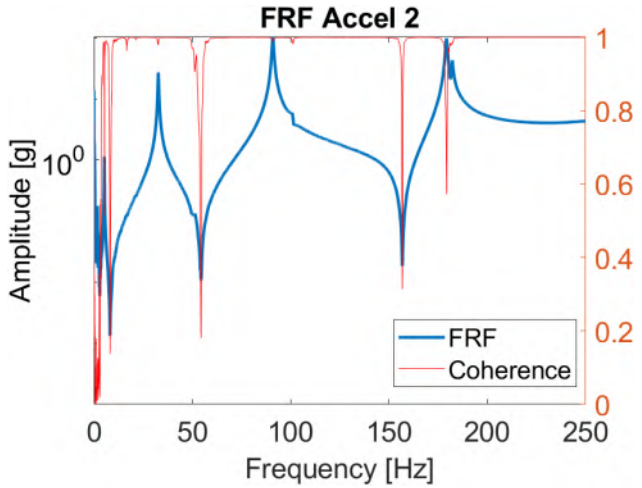
- Fs = 500Hz
- 8192 points
- ~16s of response
- Burst random excitation

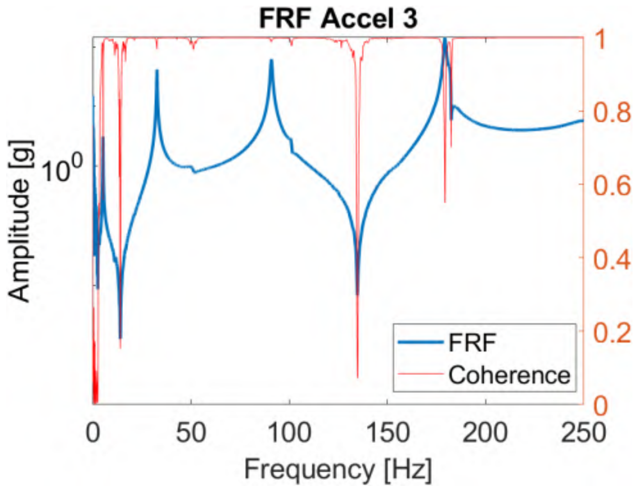


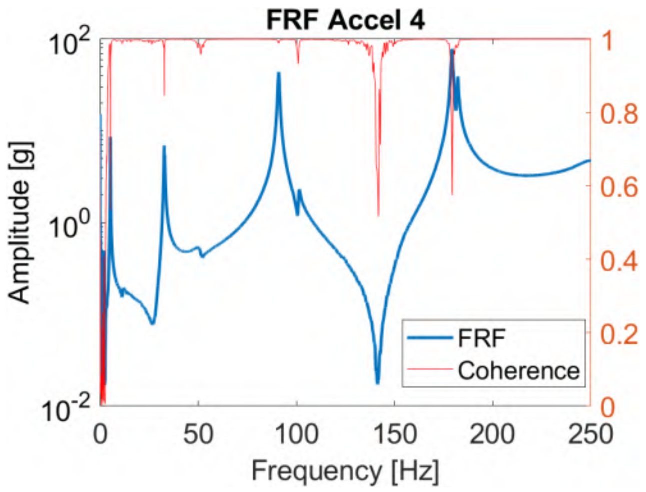
FE Modal Frequencies [Hz]
5.6718
33.188
35.425
99.525
104.67
190.57

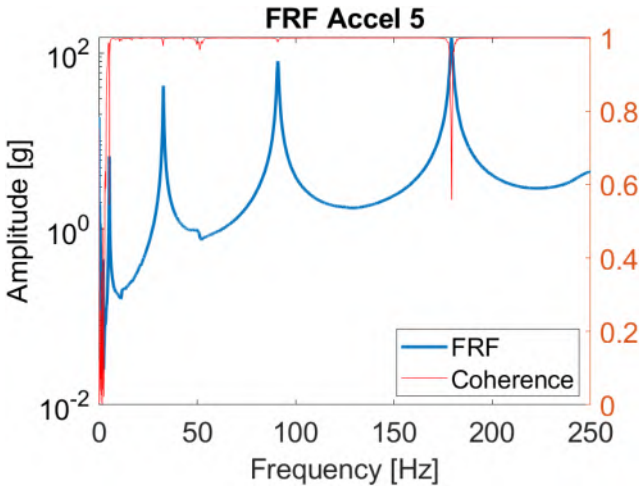
FRF and Coherence of the Plate Structure





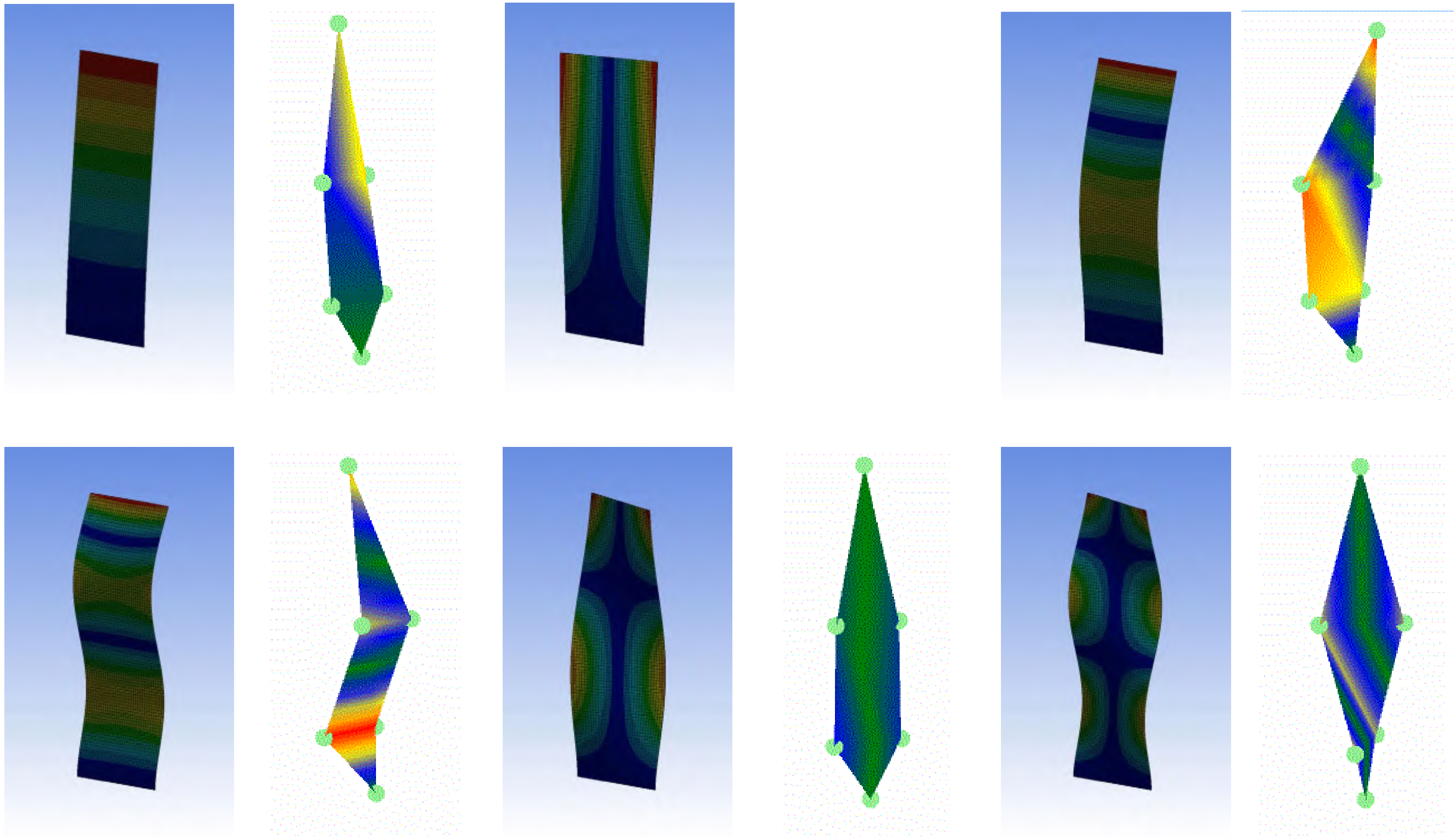




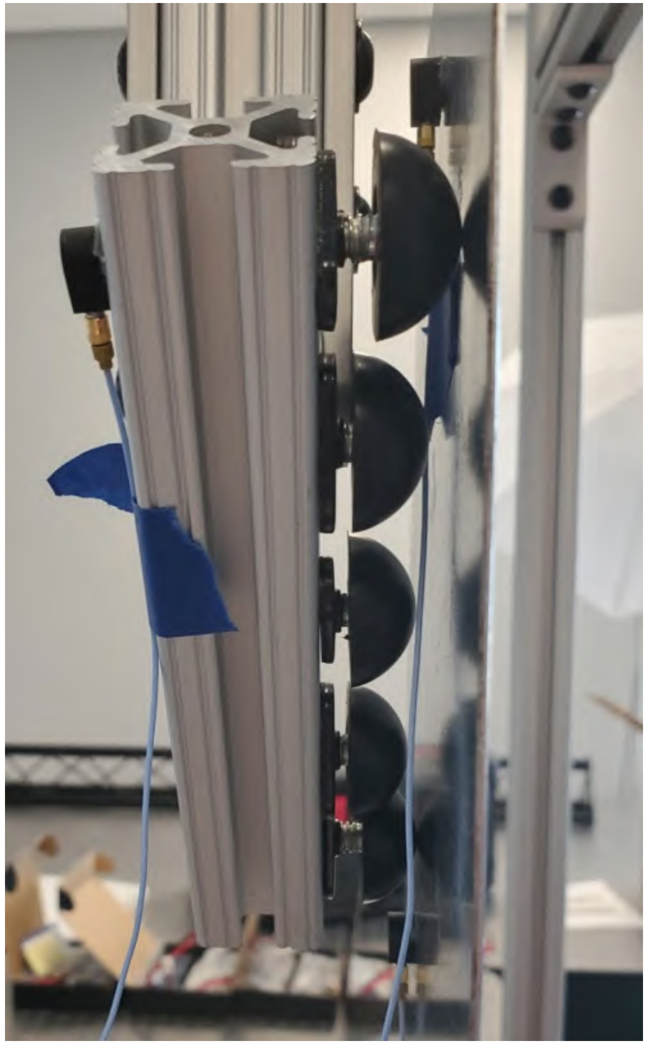


Experimental Result Compared to FEM

FEM frequencies [Hz]	Experimental frequencies [Hz]
5.6718	5.31
33.188	-
35.425	32.71
99.525	90.94
104.67	101.44
190.57	182.19

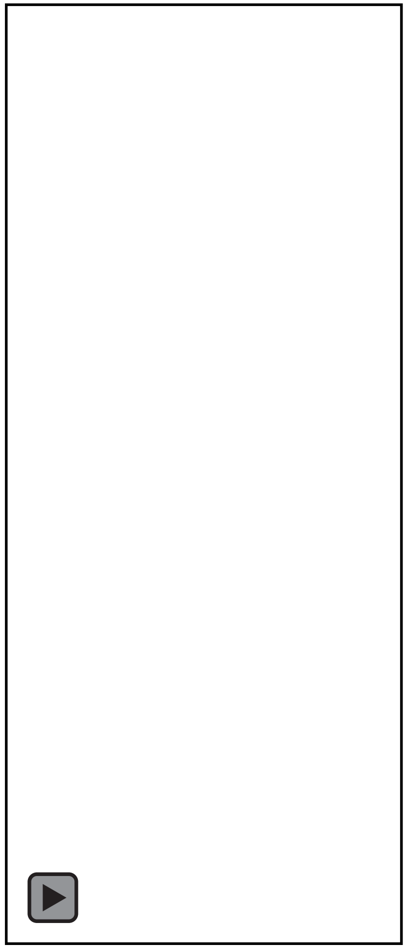


Introducing Nonlinearities

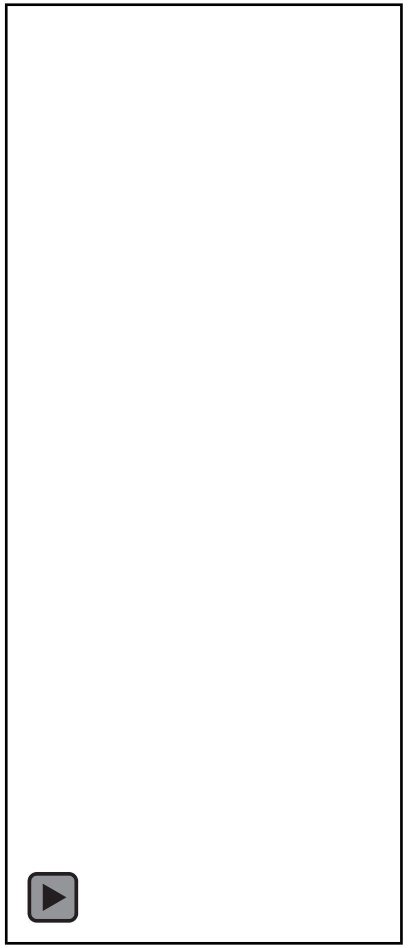


- Bumpers with adjustable gap
- Nonlinearity sources
- Controllable number of bumpers
- Different levels of excitations

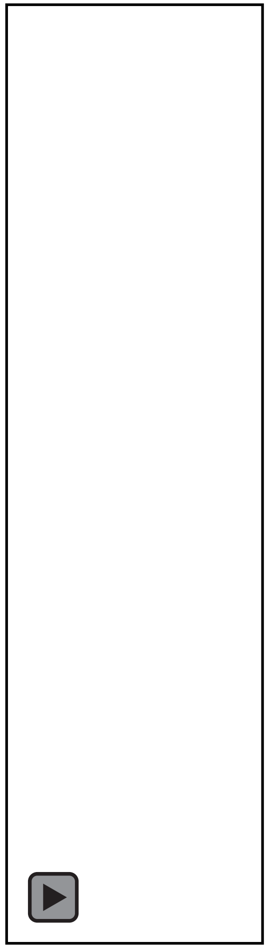
Motion Magnification on the Bumpers



3 – 15Hz bandpass
$\alpha = 20$

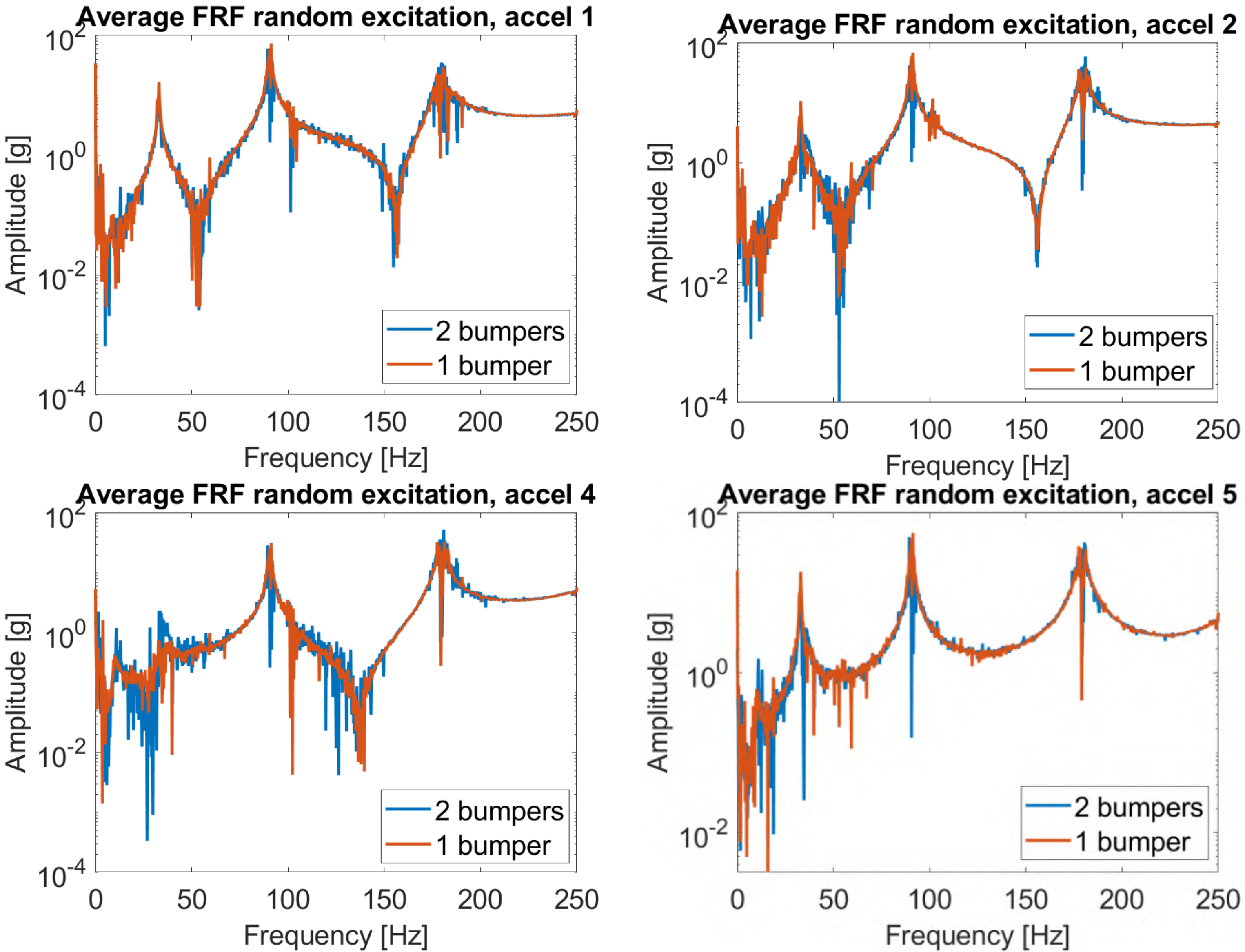


30 – 35Hz bandpass
$\alpha = 20$



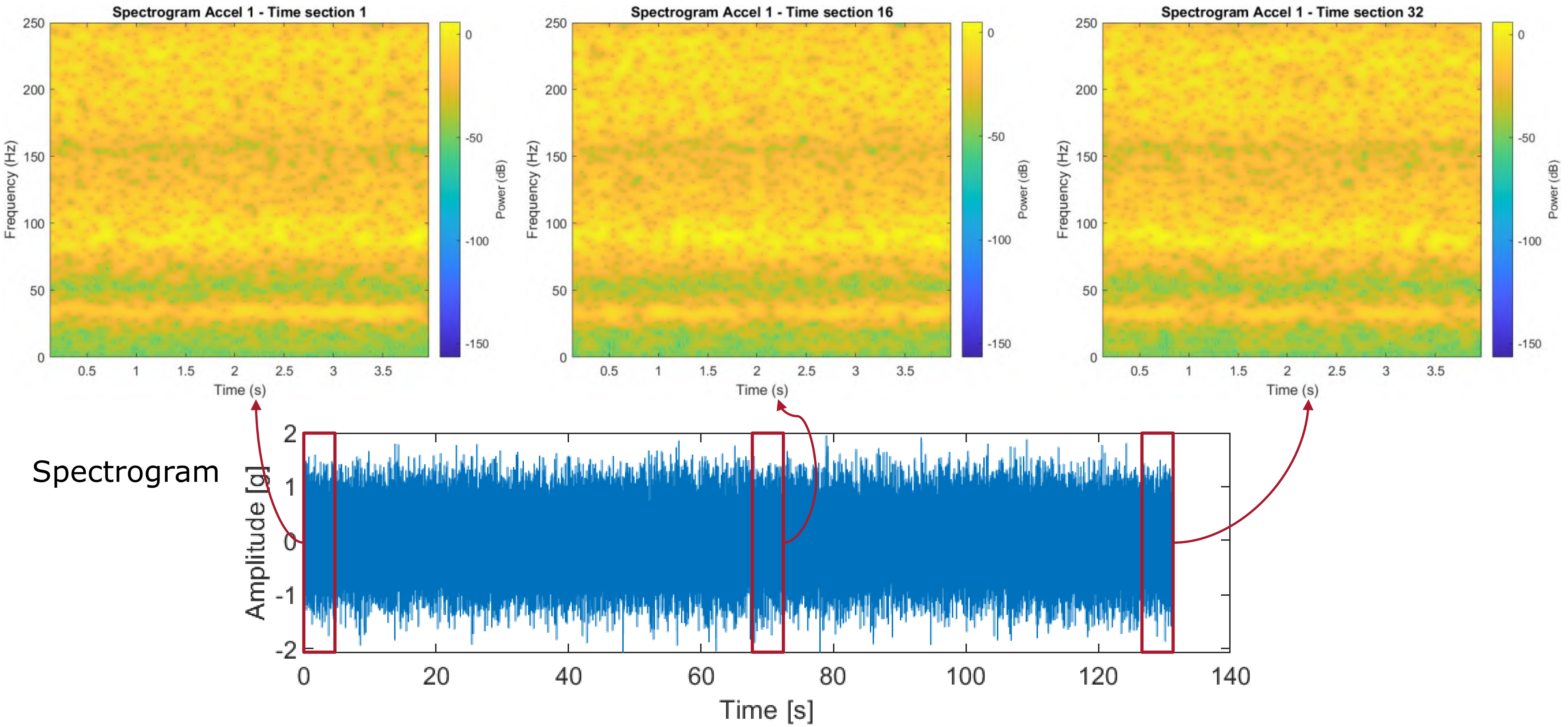
175 – 185Hz bandpass
$\alpha = 100$

FRF with Different Number of Bumpers



- Much noisier FRF estimations
- Drops of coherence

Spectrograms of the Nonlinear System



Spectrogram

Big Picture

- A plate structure with different levels of nonlinearity to generate different levels of "damages"
- Large amount of data under well-controlled environment available
  - Number of bumpers engaged
  - Amplitude of excitations
- More rigorously validate the physics-enhanced GAN approach

Acknowledgements

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