Feature extraction for defect detection utilizing Lamb waves and supervised machine learning algorithms

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Introduction

Although the aeronautical and other cutting-edge industries utilize state of the art materials and fabrication techniques, adhesive primary structures have not being used due to the lack of reliable non destructive methods for damage detection [1,2]. This work presents a methodology for detecting defects, such as weak adhesion in adhesive joints by employing Lamb waves (LW) in conjunction with machine learning algorithms.

Experimental Methodology

Finite Element Models were used in order to create the dataset required to apply machine learning. A model of a joint was created with two aluminum substrates with 150 x 150 x 2 mm and an overlap of 25 mm, where the mesh size was 1.5 mm. The adhesive simulated was Nagase T-836/R-810 with a layer of 0.2 mm, and the actuator/sensors were placed centered, at a distance of 30 mm from the edge of each substrate (Figure 1). The weak adhesion was simulated by altering the interface force between the adhesive and substrate. The LW, which are a form of guided waves, were generated using a Hanning window pulse with a frequency of 100 kHz and applied to the horizontal surface of the joint.

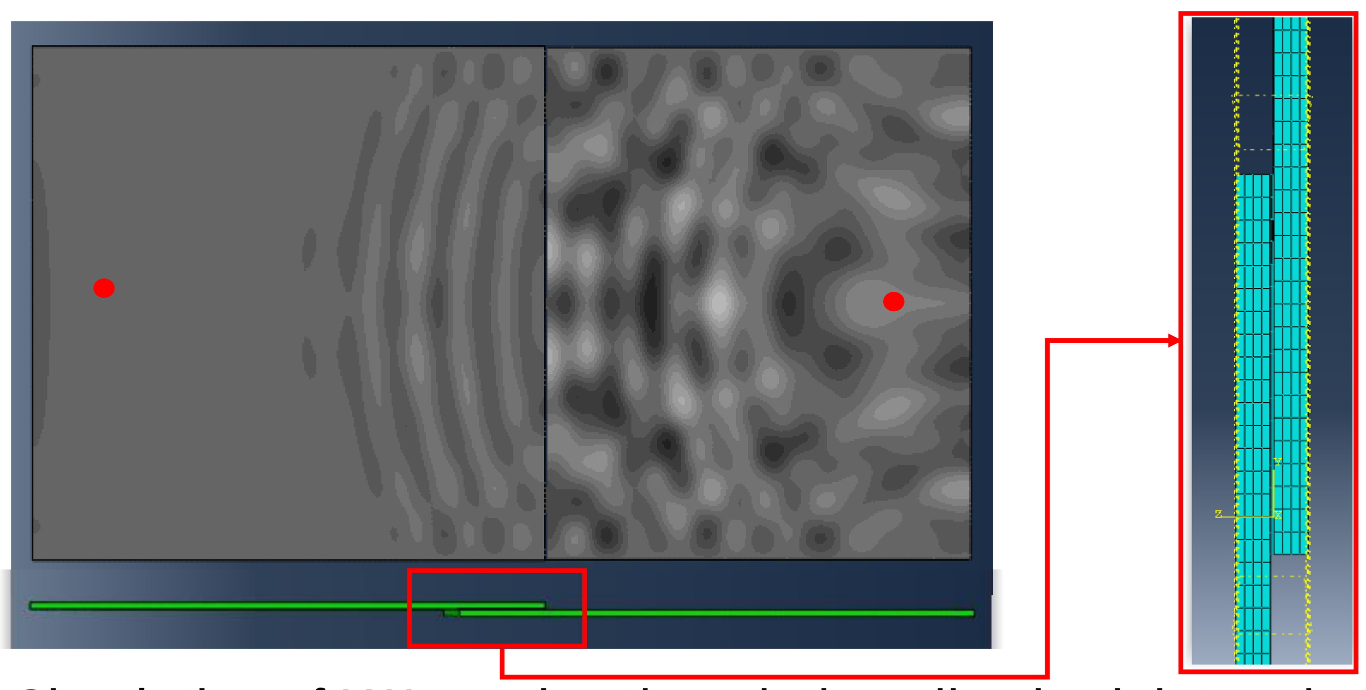

Figure 1 – Simulation of LW passing though the adhesive joint and mesh used.

Discussion

The methodology involved creating a database that was processed utilizing a Python library called Tsfresh. This library can extract over 700 features from the database. In turn, the features were visualized utilizing MDS (figure 2) and MDS techniques as a means to better understand which features could be considered more relevant.

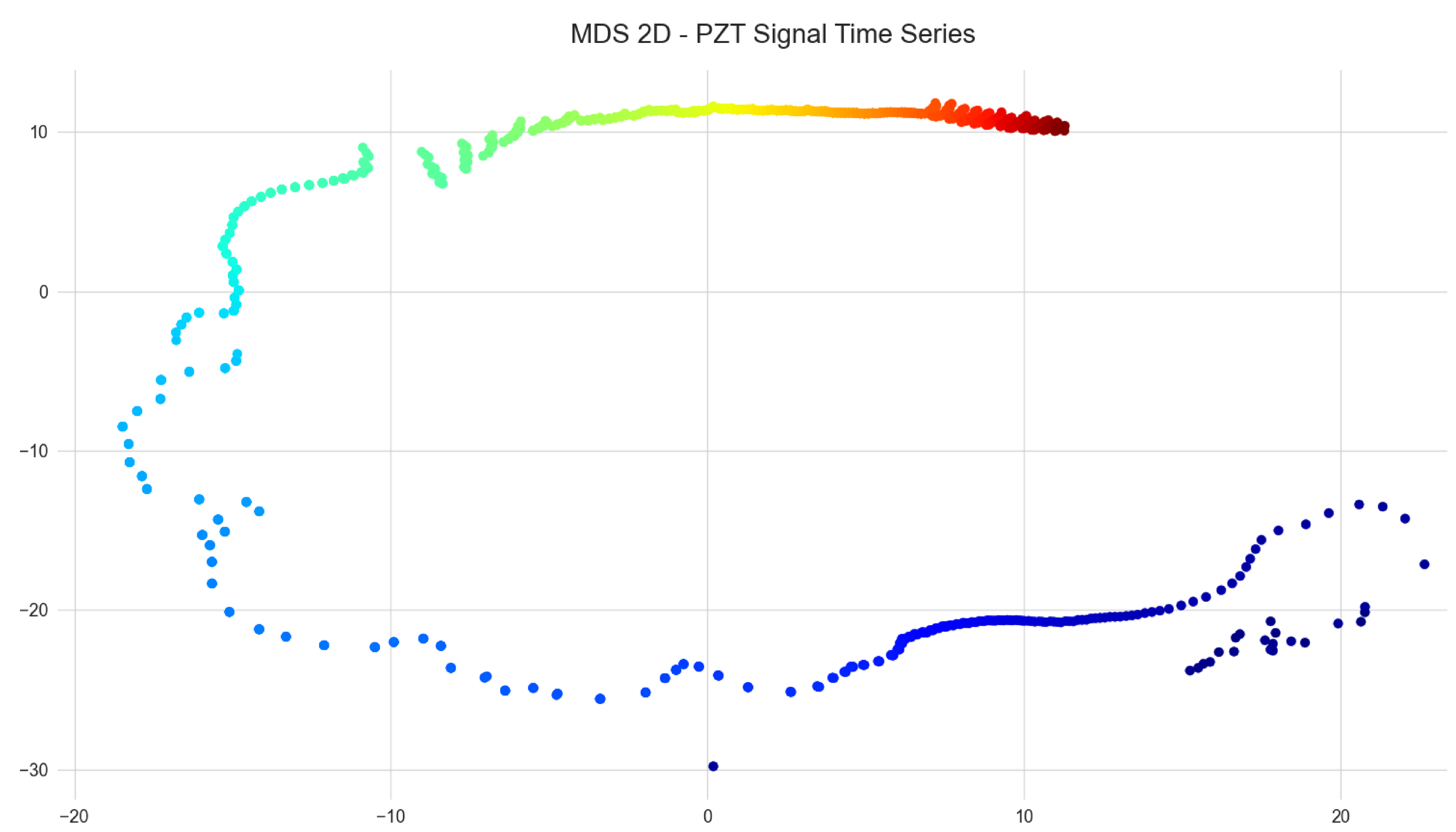

Figure 2 – Example of features extracted and visualized with MDS.

Results

The most promising features are selected, utilizing the data obtained in the visualization in combination to the Benjamini-Hochberg procedure, in order to be used in 4 machine learning models: Gaussian Naive Bayes, k-Nerest Neighbors, Gradient Boosting and Random Forest. These were chosen as a way to have a wide varaity of options to create a robust methodology that can be used in any case.

Models		Adhesive Joint Data Set		
		Full Features	Selected Features	Top Features
Gaussian Naïve Bayes	acc	0.948	0.948	0.981
	p	0.952	0.952	0.981
	r	0.945	0.945	0.982
	F1	0.948	0.948	0.982
k-Nearest Neighbors	acc	0.552	0.552	0.982
	p	0.566	0.566	0.981
	r	0.550	0.550	0.980
	F1	0.555	0.555	0.982
Gradient Boosting	acc	0.996	1.00	0.993
	p	0.997	1.00	0.993
	r	0.996	1.00	0.993
	F1	0.996	1.00	0.993
Random Forest	acc	1.00	1.00	1.00
	p	1.00	1.00	1.00
	r	1.00	1.00	1.00
	F1	1.00	1.00	1.00

Table 1 – Results obtained utilizing the most promising features in four different machine learning algorithms.

In this particular case the Random forest algorithm was able to obtain a 100% acurracy, the other algorithms obtaining over 98%. It is also important to note that the selection criteria was able to elevate the results from 55%, for the k-Nerest Neighbors, to over 98%, for the best cases (Table 1).

Conclusions

This work presented a novel methodology for feature extraction that allowed damage detection on an adhesive joint with a 100% accuracy.

References

[1] Karachalios EF, Adams RD and Da Silva LF (2013) Strength of single lap joints with artificial defects. International Journal of Adhesion and Adhesives 45: 69–76. DOI:10.1016/j.ijadhadh.2013.04.009.

[2] da Silva, Lucas F M, O¨ chsner, Andreas, Adams RD (2011) Handbook of Adhesion Technology. 1 edition. Springer-Verlag Berlin Heidelberg. DOI:10.1007/978-3-642-01169-6-1.